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Department  
for Education



# The earnings returns to postgraduate degrees in the UK

Research report

September 2020

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## Executive summary

This report provides estimates of the earnings returns to completing postgraduate degrees, for British and Northern Irish students studying in Britain. We use the Longitudinal Education Outcomes (LEO) dataset to account for differences in individuals' background and prior university attainment to estimate the impact of postgraduate qualifications on earnings at age 35, relative to having an undergraduate degree and not proceeding onto further study.

We use age 35 for our headline estimates in order to allow people to gain sufficient labour market experience after completing their qualifications. We also show how these returns evolve throughout individuals' thirties. We look separately at returns for masters, PhD and Postgraduate Certificates in Education (PGCE) degrees, and break these down by gender, prior undergraduate degree, postgraduate institution, and (where appropriate) postgraduate subject. Following our previous reports we estimate the earnings impact for individuals in sustained employment, though we additionally consider the effect on the probability of being in sustained employment and earning above certain thresholds. We focus on individuals who started their undergraduate degree by age 21 and define postgraduates as those who have completed a full-time postgraduate qualification by age 30.

While this work dramatically improves on the existing evidence in this area, some caution needs to be exercised when interpreting these findings. **First**, this report focusses on the *private earnings* returns to postgraduate qualifications only. **Second**, while we have a very rich dataset that allows us to control for many of the differences between those that do and do not attend postgraduate courses, there may still be unobservable differences between individuals which we cannot control for, such as differences in motivation or preferences over occupations or working hours. **Third**, our main estimates focus on the earnings return *at age 35*. To the extent that earnings patterns of graduates of different postgraduate degrees may diverge from individuals with only an undergraduate degree beyond this age, these returns may look different later in the lifecycle. **Finally**, our main estimates are necessarily based on individuals who graduated from their undergraduate degree between the mid-1990s and the mid-2000s. It is important to recognise that returns might be very different for current undergraduate students due to compositional and labour market changes. With these caveats in mind, we outline our main findings below:

## Who does postgraduate degrees and what are they studying?

- More and more people are proceeding onto postgraduate study. More than 350,000 students now start a postgraduate course in the UK each year, compared to only around half this number 20 years ago.
- Men are more likely to progress onto masters degrees and PhDs than women, while women are far more likely to go on to do PGCEs. Those studying for PhDs and PGCEs are disproportionately white, but the composition of masters degrees is more representative of the undergraduate population.
- Students studying for postgraduate qualifications tend to have done very well in their undergraduate degree. Virtually all PhD students, and around 70% of masters students, obtained a first class or 2:1 undergraduate degree, compared to around 50% for those whose highest qualification is an undergraduate degree. PGCE students look much more similar to undergraduates, albeit with slightly fewer first class degrees, and slightly more 2:1s.
- Individuals from more privileged backgrounds are much more likely to do a postgraduate degree, but this can be virtually all be explained by prior attainment in school and university. Even accounting for these differences however, differences remain in the type of postgraduate course attended, with individuals from less advantaged backgrounds being more likely to do a PGCE.
- Masters degrees and PhDs overwhelmingly are taken at Russell Group and pre-1992 universities, with those two groups accounting for around half of undergraduate students, but around 95% of PhDs, and 70% of masters degrees.
- Arts and humanities students are less likely than STEM students to study for a masters or PhD, but are much more likely to to a PGCE. Science, technology, engineering and maths (STEM) and Law, economics and management (LEM) students make up around 3 in every 4 masters and PhD students, even though they only account for just over 60% of those on undergraduate degrees. For PhD degrees just two subjects, biosciences and chemistry, account for around 1 in 4 of all PhD students.

## What are the average earnings returns to postgraduate degrees by age 35?

- For both men and women, masters and PhD graduates earn more on average than those with only an undergraduate degree, while PGCE graduates earn less on average. In particular for men this last gap is large, with PGCE graduates earning around £38,000 on average at age 35 compared to nearly £51,000 for those with only an undergraduate degree. For both genders earnings growth through the thirties is largest among undergraduates and PhD graduates and smallest for PGCE graduates.
- Earnings inequality varies widely across qualification groups, with very few PGCE graduates experiencing very high earnings, but also many fewer experiencing low earnings compared to those who left education after their undergraduate degree. As a result, despite the large differences in mean earnings, median earnings of PGCE graduates are very similar for men, and even somewhat higher for women, than those of undergraduates.
- Once we control for differences between students, the earnings gap between undergraduate and masters and PhD graduates drops significantly: we estimate returns of 2% (women) and -2% (men) for masters and 8% (women) and -9% (men) for PhDs.
- For PGCEs accounting for differences in background and undergraduate attainment has the opposite effect, primarily due to PGCE students having studied undergraduate subjects with lower earnings potential on average. We get a final estimate of the returns to PGCEs at age 35 of -2% for men and +1% for women.
- Our estimated returns for postgraduate degree are considerably smaller than previous estimates from the UK, which have been consistently positive. We believe this is because we have much richer data than has previously been available which allows us to much better control for differences between postgraduates and undergraduates.
- PGCEs are a relatively ‘safe’ choice for both women and men: they reduce the chances of not being in employment, as well as earning less than £30k, but decrease the probability of earning more than £40k. We see quite similar patterns for PhD degrees, as well as for masters degrees for women. Perhaps this is because these degrees tend to result in people pursuing specific interests, such as research, where salaries are reasonable, but which are not necessarily the most exceptionally lucrative careers. For men masters degrees do not offer



this insurance value.

## **How do the returns to masters and PhDs vary by subject, institution and prior qualifications?**

- The overall estimates obscure important heterogeneity in returns across subjects. Around a third of masters subjects yield statistically positive returns for women. LEM subjects give the highest returns of around 20% at age 35, but courses such as creative arts, English and philosophy lead to earnings more than 10% lower than those of similar individuals who did not pursue a postgraduate qualification.
- Returns for men by masters subject are lower, with statistically significant negative returns at age 35 for most subjects. However LEM subjects and engineering still yield strongly positive returns for men. When looking at PhD degrees there are some notable differences in the subject ordering, such as PhDs in maths having remarkably low returns and psychology being one of the highest return PhDs for both genders.
- By institution, returns for masters degrees range from less than -20% for a handful of institutions at the bottom end, to upwards of 20% at the top. However, much of these differences are driven by the subject offering of each institution, with many of the institutions at the top having large shares of students studying high returns courses such as law, while the institutions at the bottom tend to specialise in low return arts, music and drama courses.
- Prior study is also important. For individuals who have graduated from a relatively low-returning undergraduate course, the best option for maximising earnings is to diversify: while these individuals often see negative returns to a masters in the same subject, returns to a masters degree in a different field are overwhelmingly positive, both for men and women. Students who graduated with a degree in a relatively high paying subject such as economics, law, business or some of the STEM subjects, tend to do best by sticking with their subject at masters level, while switching can be particularly costly. These estimates might seem like the most pertinent for prospective postgraduate students choosing a course.
- Overall we find that for students of nearly all undergraduate subjects there are some masters subjects they can take which lead to positive returns - even for men, who see very low returns overall.

## How do the returns to PGCEs vary by institutions and prior qualifications?

- Among PGCE graduates we observe significant heterogeneity across undergraduate subjects. Notwithstanding the large negative average returns to PGCEs, for both men and women graduates of a handful of subjects - including sports science and creative arts - have large and significant positive returns to PGCEs. On the other hand, economics, law and maths graduates have large negative returns to PGCEs of -20% or more, due to the very high counterfactual earnings for this group.
- Unlike for masters and PhDs, PGCE graduates from Russell Group universities tend to have the lowest estimated returns, which is likely driven by the higher prior attainment - and hence higher counterfactual earnings - of these students, and the limited pay differentials in teaching.
- These low returns might explain the patterns of selection into PGCEs, and indeed teacher recruitment challenges: PGCEs are most prevalent among English, sports science and philosophy graduates, and much less prevalent for many STEM and LEM subjects.

# 1 Introduction

Postgraduate education has expanded rapidly in the last couple of decades, with more than 350,000 students now starting a postgraduate course in the UK each year, compared with only around half this number 20 years ago.<sup>1</sup> As increasing numbers of students consider postgraduate study, accurate information on the returns to the different options they face is essential for allowing them to make an informed decision on whether, where and what to study.

Previous evidence on the returns to postgraduate study in the UK has generally implied that the returns are quite large and positive. This, coupled with evidence of growing educational inequalities, prompted the UK government to introduce income-contingent student loans for postgraduate students in 2016/17, which added more than £600 million to government borrowing in 2018/19 alone. However, the current evidence on postgraduate returns has faced serious limitations, primarily due to data availability. High-quality evidence on the returns to these degrees is important not only for students, but also for policymakers considering the value of these loans, as well as more generally for thinking about the development of skills in the economy and the role postgraduate education might play for social mobility.

In this report, we make an important contribution towards filling the evidence gap by estimating the impact on earnings of postgraduate qualifications for individuals with an undergraduate degree. We distinguish between PGCEs, masters and PhD degrees, and show how the returns vary across subject and institution of study, as well as by the individual's undergraduate course. We make use of the novel Longitudinal Education Outcomes (LEO) data set, which has also been used in our previous work estimating the returns to undergraduate degrees (Belfield et al., 2018a). The LEO data set links school, university and tax records for the population of individuals born since 1986 who attended secondary school in England. It additionally contains linked university and tax records for those born before 1986 who attended university at any point since 1995/96, though no school records.

In order to get at the impact of postgraduate courses on earnings, we need to account for the important differences in attainment and background that influence both earnings and the probability of attending a postgraduate course. We do this by controlling for observable differences between students. In an ideal model, we would use the complete academic history of the students, including their school and university records. However, a drawback of this approach is that we

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<sup>1</sup>Numbers from HESA student numbers statistics for 2017/18 and 1997/98.

only observe earnings records up to age 30 for those with linked school records. Since many people take postgraduate degrees throughout their 20s, this will mean that at age 30 many individuals will only have just graduated from their postgraduate degree, and hence their earnings will not yet reflect their later-life earnings. Instead, we therefore use the cohorts for whom we have linked university and tax records – but not school records – which allows us to look at earnings up to age 40 rather than age 30. We perform some robustness checks to show that for 30-year-olds – for whom we do have complete school records – there is very little extra information contained in their school records once we control for differences in background and attainment based on individuals’ university records. This leads us to believe that excluding the information contained in school records does not result in biased estimates of the returns at later ages.

Although our data allow us to look at earnings up to age 40, the data quality deteriorates when looking at individuals after their mid 30s. Hence our headline estimates focus on the return to postgraduate courses at age 35, although we show how these estimates evolve at all ages between 30 and 40.

While there is a large academic literature on the returns to undergraduate degrees, this is not the case for returns to postgraduate qualifications. Much of the literature has focused on the return to specific postgraduate qualifications in the United States, such as MBAs (Arcidiacono et al., 2008; Grove and Hussey, 2011) or postgraduate law degrees (Simkovic and McIntyre, 2014). The most comprehensive study to date is recent work by Altonji and Zhong (2019), which estimates the returns to graduate degrees in the US and looks at heterogeneity by field of study. They estimate returns by comparing earnings of individuals before and after their graduate degree. We do not use this approach in the UK, as the pattern of postgraduate attendance is very different from that in the US and labour market experience before a postgraduate degree is much less common.

The existing literature in the UK mainly relies on the Labour Force Survey (LFS). Conlon and Patrignani (2011) use LFS data from 1996 to 2009 to estimate an earnings premium of 9% for masters and 16% for PhDs. Walker and Zhu (2011) also use the LFS to show there are higher returns to postgraduate qualifications for individuals with undergraduate degrees in law, economics or management. Due to the smaller sample sizes in the LFS, as well as limited background information on individuals in that data, existing work in the UK has neither been able to estimate returns to specific subjects and institutions, nor been able to fully account for differences in attainment and background between students.

We expand on this existing work by using administrative LEO data to estimate the returns to postgraduate qualifications in the UK. This data set enables us to control for a rich set of observable characteristics when estimating the labour market impacts of postgraduate qualifications. The very large number of individuals we observe allows us to investigate how returns vary across subjects and institutions of study, as well as by the individual's undergraduate degree.

While this work dramatically improves on the existing evidence, and will provide very valuable information for both policymakers and students deciding on postgraduate study, certain caveats need to be kept in mind when interpreting our results. First, in this report, we purely focus on the *private earnings* returns to postgraduate qualifications. This means we do not take into account any non-pecuniary benefits to the individual, such as access to more desirable occupations or improved health or happiness, nor do we take into account any impacts on wider society, such as working in a socially valuable occupation or increasing the productivity of workers around them. Second, while our data set allows us to control for a rich set of observable characteristics, unobservable differences between individuals may remain, such as differences in motivation or preferences over occupations or working hours. As such, our estimates should not be interpreted as definitely causal. Third, our main estimates focus on the earnings return *at age 35*. We provide evidence on how overall returns to postgraduate qualifications evolve up to age 40, but to the extent that earnings patterns of postgraduate graduates may diverge from those of individuals with only an undergraduate degree after this age, these returns may look different later in the life cycle.

The remainder of the report proceeds as follows. Section 2 describes the data and outlines some of the key facts about postgraduate students, including who they are, what they study and a brief overview of participation trends (participation trends are explored in further detail in a short briefing note “Family background and access to postgraduate degrees” accompanying this report). Section 3 provides descriptives on how much they earn. Section 4 details our regression model and Section 5 shows our estimates of the overall average returns to postgraduate degrees. Section 6 then shows heterogeneity in returns to masters and PhD degrees by subject, institution and undergraduate subject, while Section 7 looks at heterogeneity in returns to PGCEs by institution and undergraduate subject. Section 8 concludes.

## 2 Data

We use the Longitudinal Educational Outcomes (LEO) data set, generated in collaboration with the Department for Education. The LEO data link school records from the National Pupil Database (NPD), higher education records from the Higher Education Statistics Agency (HESA), tax and employment records from Her Majesty’s Revenue and Customs (HMRC) and benefits data from the Work and Pensions Longitudinal Study (WPLS).

Our previous reports (Belfield et al., 2018a,b) give more information on the data set. Those reports made use of the rich background information from the NPD records in order to account for selection into higher education. As we only have linked school records for those born in 1986 or after, this implied that we were constrained to look at earnings for ages up to 29.<sup>2</sup> In this report, however, our base sample is those who have obtained an undergraduate degree, and we estimate the return to additionally doing a postgraduate degree. Consequently, we are able to use the information contained in each student’s HESA record to control for differences between students, and do not make use of the data from individuals’ linked school records. This is clearly a trade-off, but it allows us to include earlier birth cohorts in our analysis, which means we can look at the earnings of individuals up to age 40 in 2016/17, the last year of our earnings data. This is particularly valuable as postgraduate degrees are often done at older ages, meaning age 30 would be too early to assess the earnings returns.

In this section, we first discuss how we create our sample for analysis, which is a slightly different process from that in our previous reports as we start with the HESA data rather than the NPD data. We then discuss how we define our postgraduate groups – which is necessary because people can take complicated routes through higher education – before turning to some descriptive statistics about the types of individuals who choose to study postgraduate degrees.

### 2.1 Sample selection

We estimate the returns to postgraduate qualifications relative to leaving higher education after obtaining an undergraduate degree; hence we restrict our sample to individuals who achieved an undergraduate qualification. Undergraduate ‘dropouts’ – individuals who attended university but did not graduate from their undergraduate degree – are therefore excluded from our analysis, as

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<sup>2</sup>Since the publication of those reports, we have obtained an extra year of earnings data, allowing us to estimate returns up to age 30.

postgraduate study is not a viable option for the vast majority of this group. We are interested in individuals who did their undergraduate degree relatively soon after school and hence exclude mature students and focus on those who started their undergraduate degree between the ages of 17 and 21. Our baseline sample further consists of British and Northern Irish students who studied in Britain.<sup>3</sup> We therefore exclude overseas students and UK students who did their undergraduate degrees abroad.

Our main results include earnings observations from ages 33 to 40, based on tax data from 2013/14 to 2016/17 that include earnings from both employment (from Pay As You Earn (PAYE) records) and self-employment (from Self Assessment (SA) records). As our last year of earnings data are from the 2016/17 tax year, individuals need to be born in or before the 1982/83 academic year for us to observe them at age 33 or older and be able to include them in the main analysis.<sup>4</sup>

Once we take into account these restrictions, we have a base sample of just over 1.6 million graduates in the HESA data, as shown in the first column of Table 1. The table classifies individuals into cohorts based on the year they *started* their undergraduate degree and shows that graduates in our main analysis sample will have started their undergraduate degree between 1993 and 2004. The 1993 starting cohort is the earliest HESA data we have,<sup>5</sup> and there will be no individuals whom we observe at age 33 in our data who started their undergraduate degree as a non-mature student after 2004.

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<sup>3</sup>Northern Irish universities are not included in the analysis of returns by university as we are not able to observe Northern Irish graduates who never attended any form of education in the rest of the UK. The graduates we do observe from Northern Irish universities are therefore a select sample of the student population at these universities and our estimated returns would not be representative of the true returns at these universities.

<sup>4</sup>We also show some returns at all ages from 30 to 40 as a robustness check. For these results, we are able to include additional individuals born between 1982 and 1985. The process of sample selection for these individuals is not shown here, but it is done in exactly the same way as shown below for the main analysis sample.

<sup>5</sup>The first year of HESA data we have is 1995/96. As we observe the age individuals started their degrees, we can reliably infer the birth cohort of all students starting from 1996 onwards. In addition, we can impute the birth cohort of students who graduated from their degree between 1996 and 1998 based on a degree length of three years.

Table 1: Sample selection

	(1) Base sample	(2) Quals cleaning	(3) Subject cleaning	(4) FT	(5) Linked HMRC	(6) Emp, earn & YAG
1993	141,931	141,918	135,196	128,056	85,281	64,900
1994	139,467	139,464	132,693	126,065	85,480	72,750
1995	137,728	137,713	131,373	124,721	86,322	74,064
1996	166,942	166,334	158,801	150,329	108,350	92,910
1997	174,524	173,974	167,166	158,368	117,492	100,999
1998	175,718	174,991	169,992	160,454	139,547	120,634
1999	183,794	183,014	179,170	168,931	150,864	129,445
2000	187,114	186,274	184,123	173,548	156,925	132,384
2001	189,515	188,697	186,097	175,134	160,275	131,102
2002	88,654	88,081	87,198	82,042	75,393	60,415
2003	30,272	29,809	29,160	26,320	24,073	19,068
2004	9,913	9,786	9,610	8,623	7,911	6,090
<b>Total</b>	<b>1,625,572</b>	<b>1,620,055</b>	<b>1,570,579</b>	<b>1,482,591</b>	<b>1,197,913</b>	<b>1,004,761</b>

Note: All columns give the number of unique individuals in our sample. Individuals are classified according to the year they started university. Column 1 shows the total number of British and Northern Irish students, born in or before the 1982/83 academic year, who studied in Britain and graduated from an undergraduate degree that they entered as a non-mature student in or after 1993. Column 2 drops individuals who attend postgraduate courses but do not graduate from any of them by the age of 30. Column 3 drops individuals on a few very small courses or with missing subject information. Column 4 drops individuals on part-time courses. Column 5 drops individuals who cannot be linked to the HMRC data. Column 6 drops individuals not in sustained employment with positive earnings at any point in the tax data from 2013/14 to 2016/17 when they are between ages 33 and 40 and have graduated at least three years previously (YAG stands for years after graduation).

The subsequent columns in Table 1 outline how we go from this set of UK undergraduates to our final estimation sample, broken down by cohort. In column 2 we drop individuals who attend postgraduate courses but do not graduate from any of them before the age of 30. In column 3 we drop individuals from a few very small subjects<sup>6</sup> as well as some individuals with missing subject information.<sup>7</sup> While the outcomes of those studying for part-time degrees are an important and interesting area of research, they are not the focus of this current report; hence in column 4 we restrict the sample to those who did full-time degrees. To perform our analysis, we need individuals' earnings records; hence we drop anyone whom we cannot link to the HMRC data in column 5. While for the later cohorts we are able to match more than 90% of individuals from HESA to the tax data, this match rate is much lower for the earlier cohorts where the quality of the HESA data is not as good as for the later years.

Finally, in column 6 we keep individuals who have graduated at least three years ago, whom we observe in sustained employment<sup>8</sup> and with positive earnings between the ages of 33 and 40 at

<sup>6</sup>Namely, 'humanities non specific', 'combined' and Celtic studies.

<sup>7</sup>Subject studied is unknown for around 10% of first-degree students leaving university before 2003. As many of those individuals will also have missing information on age and year of birth and hence will not be included in our base sample, the share of our sample dropped in this step, due to missing subject information, is lower than 10%. For virtually all students leaving university from 2003, we are able to link them to the subject(s) they studied.

<sup>8</sup>Sustained employment is a variable generated by the Department for Education and is defined as being in



any point in the earnings data.<sup>9</sup>

Table 2: Number of observations and individuals in sample

	No. of unique individuals	No. of observations
Female	465,952	1,291,614
Male	538,809	1,579,701
<b>Total</b>	<b>1,004,761</b>	<b>2,871,315</b>

Note: The first column gives the unique number of individuals included in our main analysis sample, the second column gives the number of observations included. As we use the 2013/14 to 2016/17 tax years, we are able to include up to four earnings observations for some individuals, although, as can be seen, the average is closer to three per individual.

As we include four years of tax data (2013/14 to 2016/17), we will be able to include multiple earnings observations for many individuals. Table 2 shows the total number of individuals in our main analysis sample as shown in the final column of the previous table, as well as showing the total number of earnings observations we are able to use, further splitting these by gender.

## 2.2 Defining highest qualifications

Throughout, we classify individuals by the highest qualification they have obtained by the age of 30. We classify individuals uniquely into one of four groups: undergraduates (UGs), PGCEs, masters and PhDs. We classify a PhD as a higher qualification than masters and PGCEs, and masters as higher qualifications than PGCEs. However, the exception to this is when an individual’s most recent qualification is a PGCE, in which case we classify them as having a PGCE as highest qualification, even if they also have a masters or PhD. We have chosen this definition as doing a PGCE after another qualification reflects a clear move into teaching, and because the earnings patterns for this group more closely resemble those of PGCE graduates than those of masters or PhD graduates.

In classifying individuals according to their highest qualification, we take into account the first degree an individual has obtained in each qualification level (UG, PGCE, masters and PhD). It is therefore the case that when we look at heterogeneity by subject and institution in Sections 6 and 7, we take the institution and subject of the first degree obtained at their highest qualification. If, for example, an individual were to obtain a PhD in computer science after having obtained a PhD in maths, we will classify this person as having a PhD in maths. We do this as in many of these employment in five out of the last six months of the tax year, or having a self-assessment record.

<sup>9</sup>We only make use of the data from 2013/14 to 2016/17 as these are the only years for which we have self-employment income. As self-employment becomes an increasingly important part of earnings as individuals age, we felt it would be misleading to show age 35 returns estimates excluding self-employment earnings.

instances the individual may have been able to do the later qualification as a result of doing the first qualification (although in practice this decision is unimportant for our results as it affects few individuals).

Table 3 shows the possible qualification paths, and the resulting highest qualification we record. One in every four individuals in our sample obtains a postgraduate degree by the age of 30. Close to 8% of our sample has a PGCE as their highest qualification, with fewer than one in every ten of these individuals having done a masters or PhD degree before their PGCE. Of those recorded as having a masters as their highest qualification, virtually all only have a masters degree, with less than 1% having done a PGCE previously. PhDs are the least common postgraduate qualification in our sample, with less than 3% of our sample having this as their highest qualification. For these individuals it is however very common to have further postgraduate qualifications, with around half having a masters or PGCE qualification in addition to their PhD.<sup>10</sup>

Table 3: Qualification routes and resulting highest qualification

Highest qualification	Proportion of sample	Qualification route taken	Proportion of qual level
UG	77%	UG only	100%
PGCE	8%	UG → PGCE	92%
		UG → masters and/or PhD → PGCE	8%
Masters	13%	UG → masters	99%
		UG → PGCE → masters	1%
PhD	3%	UG → PhD	53%
		UG → masters and/or PGCE → PhD	45%
		UG (→ PGCE) → PhD → masters	2%

Note: The ‘Qualification route taken’ column shows the possible qualification paths individuals take based on only counting the first qualification obtained at each qualification level. The arrows indicate the chronological order in which qualifications are taken. For example, ‘PGCE → masters’ means that the masters qualification is taken after the PGCE qualification, while ‘masters → PGCE’ implies the masters qualification is taken first. The sample is based on column 6 of Table 1.

### 2.3 Who does postgraduate degrees?

We now consider the background characteristics of those doing postgraduate degrees. Tables 4 and 5 give a sense of the rates of progression of different types of individuals to different postgraduate qualifications. This is shown by highest qualification obtained by age 30, grouping together different qualification routes as defined in Table 3.

Table 4 shows the continuation rates by gender, by POLAR quintile (which measures the

<sup>10</sup>We here only record postgraduate degrees where we observe the individual obtaining a qualification. If, for example, an individual starts on a masters course and this is turned into a PhD course after successful completion of the first year(s) without awarding a formal masters qualification, this will not be recorded in Table 3 as the individual having received a masters degree prior to their PhD.

university participation rates of people from the local area an individual lived in when they applied to university for their undergraduate degree)<sup>11</sup> and by ethnicity. For reference, Appendix Table A1 gives the overall summary statistics across the whole sample of graduates (including those who do not continue to postgraduate study). It shows that just over half (54%) of the sample are male, most come from high participation areas (60% come from the top two quintiles and 36% from the top quintile) and 84% are white. This highlights an important point: these numbers are based on university entrants from the mid 1990s, and since then the share of women attending has overtaken the share of men, and the student population has become more ethnically diverse. These demographic changes suggest that returns might be different for more recent cohorts.

Table 4: Continuation to postgraduate study by background characteristics

	UG	PGCE	Masters	PhD
<i>Gender</i>				
Female	74.3	11.0	12.3	2.4
Male	78.5	4.8	13.8	2.9
<i>Participation</i>				
POLAR Q1 – lowest	77.5	9.5	10.6	2.4
POLAR Q2	77.3	8.9	11.3	2.5
POLAR Q3	77.1	8.2	12.2	2.5
POLAR Q4	76.7	7.6	13.0	2.7
POLAR Q5 – highest	75.7	6.6	14.9	2.8
<i>Ethnicity</i>				
Black	80.6	4.5	13.9	1.0
Asian	77.4	4.1	17.0	1.5
White	75.6	8.5	13.0	2.9
Other/missing	88.0	2.5	7.9	1.6
<b>Total</b>	76.5	7.7	13.1	2.7

Note: The sample is based on column 6 of Table 1.

The top panel of Table 4 shows that men are more likely to progress to masters (13.8% progress vs 12.3% of women) or PhD qualifications (2.9% vs 2.4%). However, the opposite is true for PGCEs, which are heavily dominated by women (just 4.8% of male graduates progress to a PGCE compared with 11% of women). As a result, fewer men progress on to any form of postgraduate study.

The second panel shows that *conditional* on graduating from an undergraduate degree, coming from a different POLAR background has a small, but not dramatic, effect on the probability of continuing to postgraduate study. However, as for gender, there are large differences in the type

<sup>11</sup>We are constrained to using this imperfect measure of socio-economic status by the fact that we are relying on HESA data for our background characteristics – as described above, we do not have NPD data for those who took their GCSE exams before 2002.

of progression: 9.5% of those from the lowest participation areas (the bottom POLAR quintile) go on to complete a PGCE, while 13% obtain a masters or PhD. On the other hand, only 6.6% of those from the highest participation areas go on to get a PGCE, while almost 18% obtain masters or PhDs.

The final panel of Table 4 describes continuation rates by ethnicity. We see there are still large differences in progression rates. White graduates are the most likely to progress to postgraduate study (24.4% get a postgraduate qualification by age 30, compared with fewer than 20% of black students). They are also around twice as likely to obtain a PhD or PGCE as highest qualification as other groups, but are less likely to have a masters degree as highest qualification than black or Asian undergraduates.

Table 5: Continuation to postgraduate study by undergraduate degree characteristics

	UG	PGCE	Masters	PhD
<i>Degree class</i>				
1st or distinction	57.7	5.4	23.1	13.8
2:1 or merit	72.2	8.9	16.1	2.9
2:2 or undiv 2nd	82.1	8.1	9.3	0.4
3rd, 4th, non-honours	90.5	4.5	4.8	0.2
Unclassified or other	89.2	2.9	7.3	0.6
Missing	88.2	2.5	8.6	0.7
<i>University type</i>				
Russell Group	66.3	7.7	20.3	5.7
Pre-1992	71.8	9.0	15.9	3.3
Post-1992	84.9	6.4	8.1	0.6
Other	84.7	9.1	5.9	0.3
<i>Subject group</i>				
STEM	73.1	6.4	15.3	5.1
LEM	85.1	3.1	11.5	0.3
Other	76.0	11.6	11.4	1.0
<b>Total</b>	76.5	7.7	13.1	2.7

Note: The sample is based on column 6 of Table 1. We include those with unclassified or missing degree class as graduates because we observe them having been awarded their degree in the HESA data. A list of the universities included in each university type is provided in the online appendix.

Table 5 then considers the qualifications students go on to achieve by the characteristics of their undergraduate degree. As expected, we see an extremely strong prior attainment gradient. More than 40% of individuals who obtained a first-class undergraduate degree go on to further study, compared with less than 30% of those with a 2:1 degree, and less than 20% of those who obtained a 2:2 or below in their undergraduate degree. We see these same patterns repeated if we look at the university type an individual attended for their undergraduate degree. A third of

Russell Group undergraduates go on to obtain a postgraduate qualification, while only around 15% of those graduating from post-1992 or ‘other’ institutions do so.

In the final panel of Table 5, we see that science, technology, engineering and mathematics (STEM) graduates have by far the highest propensity to stay on to do a masters or PhD.<sup>12</sup> This is partially driven by the large fraction of these students staying on to do integrated masters courses. It is important to note that whether individuals stay on for further study, especially for PhDs, is likely to reflect the funding opportunities available to students.

Finally, we see that students with an undergraduate degree in law, economics or management (LEM)<sup>13</sup> are extremely unlikely to go on to get a PGCE – only 3.1% of these graduates do so, compared with 11.6% of those with an other social science, arts or humanities degree. This is likely to at least partially reflect very different outside options for these groups.

## 2.4 Are there large socio-economic gaps in postgraduate participation?

As discussed above, students on postgraduate courses disproportionately come from more privileged backgrounds. As shown in Appendix Table A1, 41% of those with a masters degree and 38% of those with a PhD come from an area in the top POLAR quintile. However, while those from lower participation areas are somewhat less likely to progress to masters or PhDs than their counterparts from higher participation areas (see Table 4), this does not fully explain these large differences. Much of these socio-economic gaps seems to arise earlier in the system. Indeed, even among undergraduates who do not go on to take a postgraduate qualification, 36% come from areas in the top POLAR quintile and only 8% from areas in the bottom POLAR quintile.

The socio-economic gaps in postgraduate participation might have serious implications for social mobility, and understanding what explains these gaps is important in order to be able to enact the right policies to reduce them. For example, the impact of any tuition fee change would be limited if the participation gap is driven by socio-economic gaps earlier in the education system rather than by financial barriers.

In this subsection, we therefore investigate gaps in postgraduate participation. These participation trends are explored in further detail in a short briefing note “Family background and access to postgraduate degrees” accompanying this report. We examine gap in participation using the

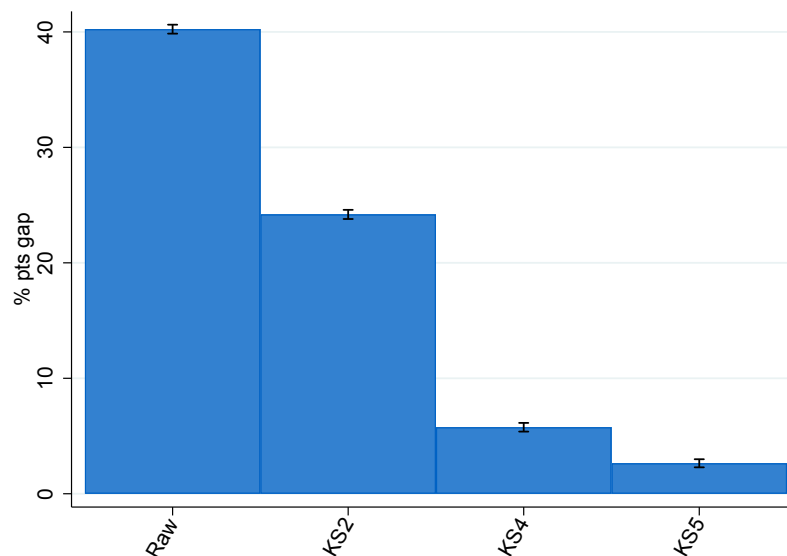
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<sup>12</sup>Appendix Table A2 further splits these subject groups and gives the highest qualification of individuals by their detailed undergraduate subject.

<sup>13</sup>We use this acronym to follow previous studies – for example, Walker and Zhu (2011) – but note that ‘management’ consists primarily of business.

cohort of students who took their GCSE exams in 2002. As this is a different cohort of students than those used in the descriptives of the previous section, Table A3 in the Appendix shows the participation rates of this cohort of students by quintile of socio-economic status (SES)<sup>14</sup>. This is a slightly younger cohort than is used in our analysis of returns to postgraduate degrees, but is the first cohort for whom we have linked school records. This allows us to use a more detailed measure of SES that takes into account several area-level deprivation measures in addition to an individual level indicator of Free School Meals (FSM) status (see Appendix Section B for more detail on this measure), and to look at gaps in postgraduate participation conditional on attainment during school. Appendix Section B gives more detail on the data and methodology used in this subsection. As we have HESA data up to academic year 2015/16, we are able to observe whether an individual has started an undergraduate or postgraduate degree by the age of 30.

Figure 1: Gap in UG participation, bottom vs top 20% of SES



Note: Results for the 2002 GCSE cohort, using English state-school students only. SES is based on several measures combined into one continuous index, as described in more detail in Appendix Section B. The first bar shows the raw percentage points gap in UG attendance between those from the top and bottom 20% of parental SES. The KS2, KS4 and KS5 bars add controls for age 11, 16 and 18 test scores respectively. See Appendix Section B for a full list of the controls included in each of the specifications. UG access is based on starting any standard UG degree course by age 30.

We start by considering access to undergraduate study in Figure 1. The first bar shows the raw gap in undergraduate participation for the 2002 GCSE cohort between the richest 20% and the poorest 20% of state-educated students. This uses a similar methodology to that used in Crawford

<sup>14</sup>We are only able to define an SES index for state school students. Private school students are therefore shown in a separate category.

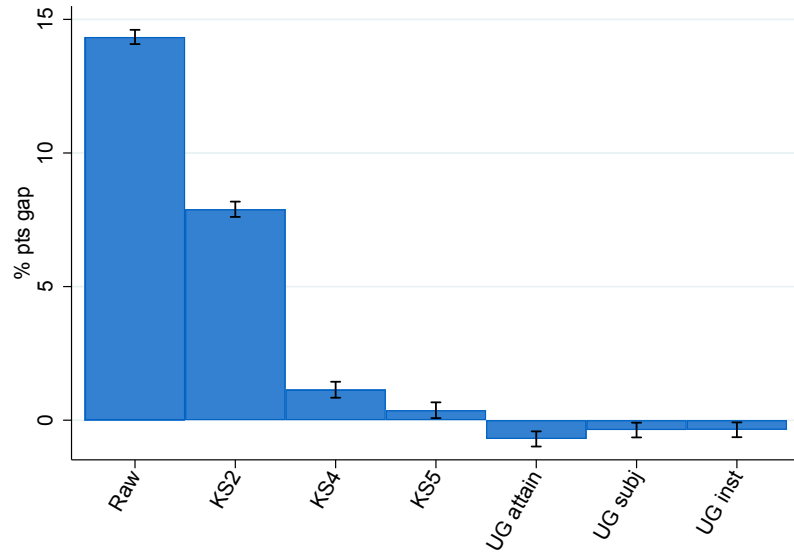
et al. (2016) but using an earlier cohort. We show that there is a raw participation gap of 40 percentage points (ppts). This declines to 24ppts once we account for socio-economic gaps in KS2 (age 11) test scores, 6ppts once we control for differences in KS4 (GCSE) scores, and 3ppts once we control for KS5 (A level) scores. This suggests that the vast majority - but not all - of the socio-economic gap in UG participation is explained by differences in prior attainment between children from different socio-economic backgrounds which arise in school.<sup>15</sup> We shown that a similar pattern holds for access to Russell Group universities in Appendix Figure A3 .

In Figure 2, we turn to doing a similar decomposition of participation gaps in postgraduate participation. The leftmost bar shows that participation is almost 15ppts higher for those coming from the wealthiest 20% of households (excluding the privately educated) than for those from the poorest 20%. While nearly 1 in 5 children with parents in the top 20% of SES attend a postgraduate course, only around 1 in every 20 children from the bottom 20% of SES do. Accounting for the differences in test scores at age 11 nearly halves this gap. Further accounting for differences in test scores at age 16, and again at 18, reduces the remaining gap considerably to less than 1 ppts. Once we account for differences in undergraduate subject, university and degree class, the gap actually reverses, and those from the bottom 20% of SES are actually ever so slightly more likely to attend a postgraduate course.

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<sup>15</sup>The findings here are slightly different from those in Crawford et al. (2016) which suggest slightly smaller initial gaps that reduce to zero with the inclusion of KS4 scores. We note, however, that they use a slightly different measure of socio-economic status. In addition, they use the 2008 GCSE cohort rather than the 2002 GCSE cohort and include additional controls for age 7 test scores in the controls (we also look at access to UG up to age 30 here, although that likely affects the results in the opposite direction).

Figure 2: Gap in PG participation, bottom vs top 20% of SES



Note: Results for the 2002 GCSE cohort, using English state-school students only. SES is based on several measures combined into one continuous index, as described in more detail in Appendix Section B. The first bar shows the raw percentage points gap in PG attendance between those from the top and bottom 20% of parental SES. The KS2, KS4 and KS5 bars add controls for age 11, 16 and 18 test scores respectively. ‘UG attain’ controls for UG degree class, ‘UG subj’ adds UG subject controls and ‘UG inst’ additionally controls for institution attended for UG. See Appendix Section B for a full list of the controls included in each of the specifications. PG access is based on starting any PG course by age 30.

This suggests that once we fully account for the differences in prior attainment in school and undergraduate degrees between student from more and less well off families, those from the poorest backgrounds are no less likely to go on to postgraduate study than those from the richest backgrounds. This result is perhaps surprising, in particular given that for this cohort of students loans for postgraduate courses did not yet exist, and hence we may have expected some difference in access to remain between the two groups, even conditional on prior attainment, driven by credit constraints.

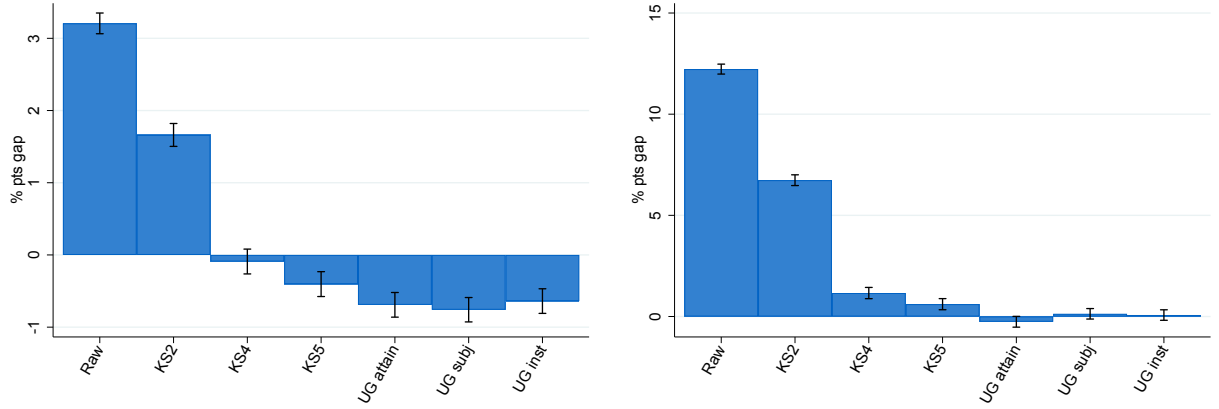
Figure 2 does, however, obscure important differences in the *type* of postgraduate courses these individuals attend. As discussed in the previous subsection, there appear to be important differences in the shares of different types of students doing PGCEs vs masters degrees or PhDs.

Figure 3 breaks this down, investigating the participation gaps in PGCE access on the left, and gaps in access to masters and PhD courses on the right (we do not have a sufficiently large sample to break out PhD students for this analysis). We see that as was the case with the probability of attending any postgraduate course, those from the poorest families are less likely to do a PGCE than those from the wealthiest families. However, once we account for attainment up to age 18, this



gap not only disappears, but actually reverses, and those from less well-off families are significantly *more* likely to do a PGCE course, conditional on having the same set of test scores up to age 18. Taking into account differences in undergraduate attainment further increases this gap.

Figure 3: Gap in participation, bottom vs top 20% of SES: PGCE (left) and masters/PhD (right)



Note: As for Figure 2.

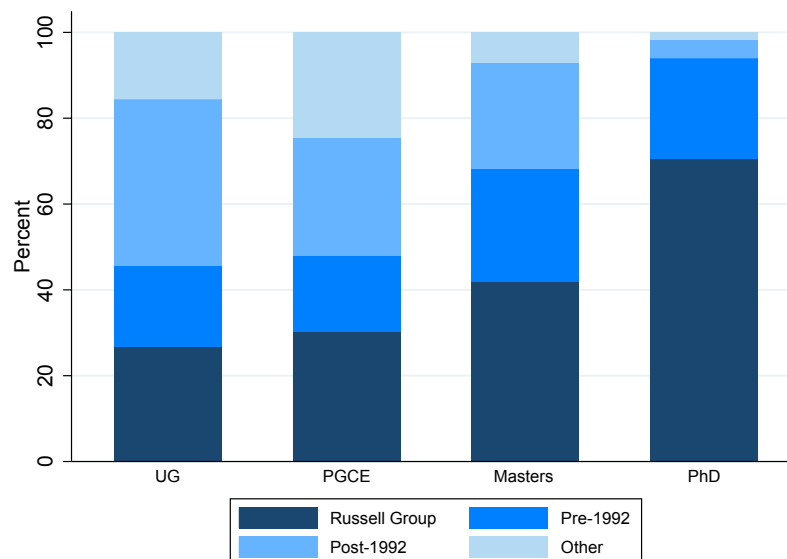
The gap in participation for masters and PhD degrees is much larger in magnitude (more than 12ppts compared with around 3ppts for PGCEs) but is also reduced dramatically once we account for all the differences in prior attainment. Including differences in undergraduate attainment reduces this gap to zero. This implies that the gaps in masters and PhD participation are indeed *entirely* explained by previous attainment. This analysis does not inform us about more recent gaps in access, which may have increased with rises in postgraduate tuition fees since the late 2000s. Understanding this, and indeed the role of the government’s new loans for postgraduate students introduced in 2015/16, is an important topic for future research.

## 2.5 Where and what are postgraduate students studying?

We now return to considering the overall population of postgraduate students, focusing on where and what they are studying at *postgraduate* level (earlier we considered their background characteristics as well as the types of course they had done at *undergraduate* level). Figure 4 shows the distribution of where students attended university for their highest qualification. While over half of students with an undergraduate qualification as their highest qualification study at a post-1992 or ‘other’ university, this is only true for around one-third of students on masters courses and for around 5% of those studying for PhDs. PhD and masters graduates are much more likely to study at a Russell Group university. While only about one in four undergraduates study at a Russell

Group university, around 40% of masters students and nearly three in four PhD students do so. For PGCEs, the distribution of university types looks a lot like the distribution for undergraduate-only students.

Figure 4: Postgraduate university type by highest qualification

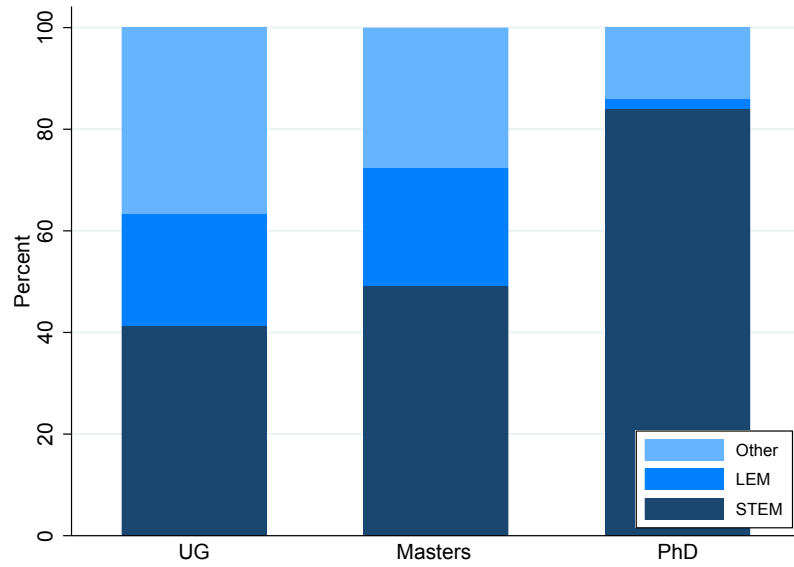


Note: University type is based on where the individual studied for their highest qualification. A list of the universities included in each university type is provided in the online appendix. Highest qualification is as defined in Section 2.2. The sample is based on column 6 of Table 1.

Figure 5 shows the subject studied in the individual's highest qualification.<sup>16</sup> We see that science, technology, engineering and maths (STEM) and law, economics and management (LEM) students make up just over 60% of students who do not go on to postgraduate study, but account for around three in every four masters students. Among PhDs, the proportion on STEM courses is even higher, with over 80% of PhDs being in STEM courses and just two subjects, biosciences and chemistry, making up around one in four of all PhD students. LEM subjects, while being relatively common masters courses, account for only a very small fraction of PhD courses. It is important to note here that, particularly for PhDs, the subjects taken are likely to reflect the funding opportunities available to students.

<sup>16</sup>Appendix Figure A1 further splits this by a more refined subject level. For this, we use the Common Aggregation Hierarchy level 2 (CAH2) classification. See [www.hesa.ac.uk/innovation/hecos](http://www.hesa.ac.uk/innovation/hecos) for more detail on this subject classification and for a mapping of CAH2 to the older JACS codes.

Figure 5: Subject group by highest qualification



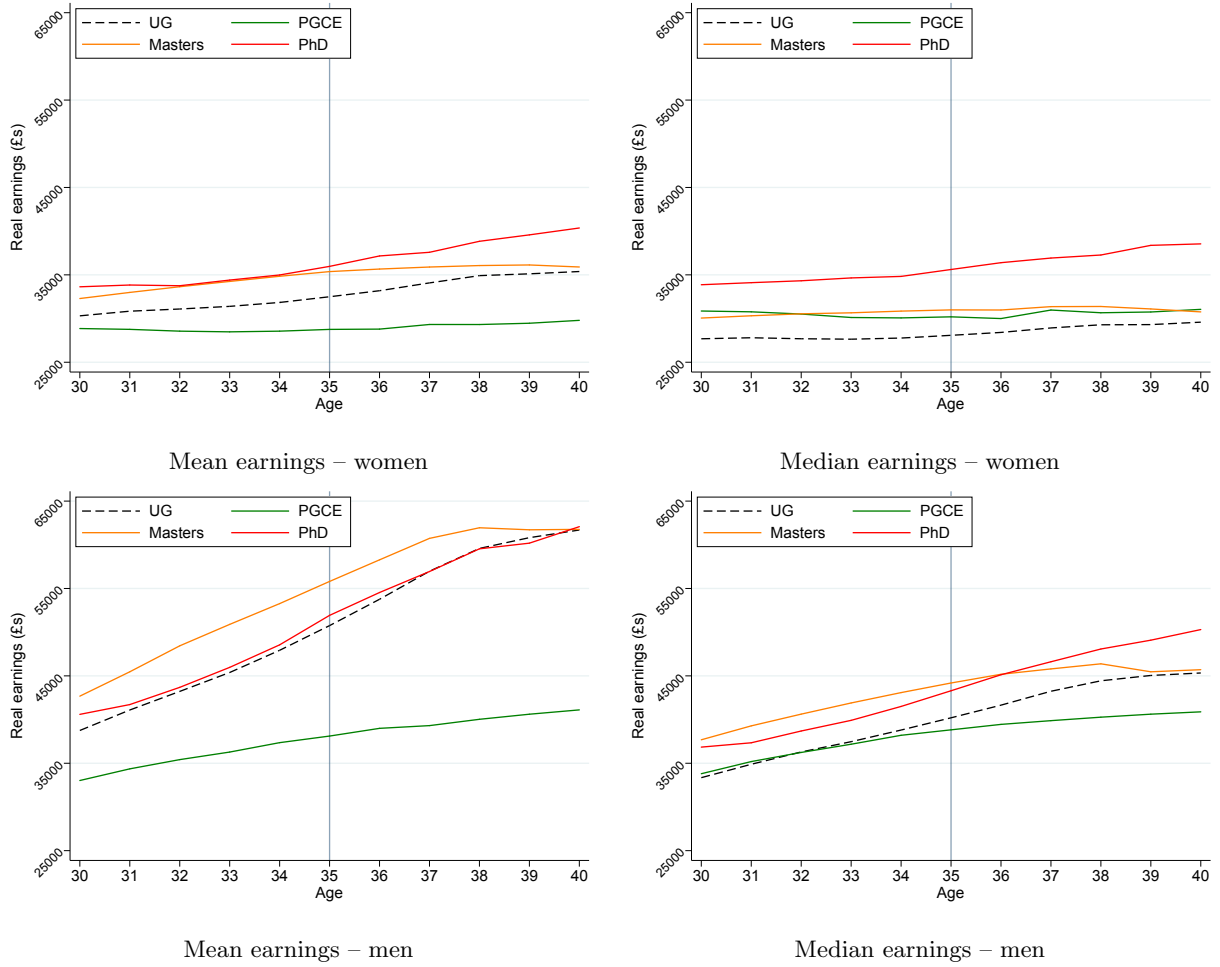
Note: Subject group is based on what the individual studied for their highest qualification. Highest qualification is as defined in Section 2.2. The sample is based on column 6 of Table 1.

### 3 How much do postgraduate students earn?

We now turn to consider the earnings of individuals with different postgraduate qualifications. Figure 6 shows how male and female earnings evolve between ages 30 and 40 by highest qualification, as defined previously. The figure pools across the years for which we have both employment and self-employment earnings (2013/14 to 2016/17), meaning the earnings profiles are comparing different cohorts at the same time rather than tracking one cohort over time. This means these descriptive plots do not take account of possible cohort effects, which might explain some of the patterns that we observe.<sup>17</sup> As in our analysis, we only include individuals in sustained employment and with positive earnings.

<sup>17</sup>For example, the growth in average earnings for women with PhDs could indeed reflect earnings growth as women with PhDs age and gain more work experience. However, it could also be driven by differences in the cohorts: if earlier (older) cohorts were a very select set of elite women while the later (younger) cohorts were a less stellar, more mixed group, this would also create a positive slope with age even if there is no underlying age effect. The following discussion assumes that the cohort effects are essentially zero, but the possibility that they are not zero should be kept in mind.

Figure 6: Earnings for those in work by highest qualification



Note: Highest qualification is as defined in Section 2.2. The sample is based on all individuals in column 6 of Table 1 who are in sustained employment and have positive earnings as well as additional individuals who were born in the academic years 1983/84 to 1985/86 for ages 30 to 32. The plots include both PAYE and SA earnings, pooling across the years where we observe both of these (2013/14 to 2016/17). This means the earnings profiles are comparing different cohorts at the same time rather than tracking one cohort over time. All earnings are in 2018/19 prices.

For women, average earnings differences between the different education groups are relatively small at age 30, with PhD graduates earning the most, followed by masters graduates and those with only an undergraduate degree. PGCE graduates have the lowest average earnings at all ages between 30 and 40. When we look at median earnings, however, the story is a little bit different (see the top right-hand panel of Figure 6). Median earnings of PGCE graduates are higher than those of undergraduates and nearly as high as those of masters graduates. This pattern is driven by the distribution of earnings: there is much less earnings inequality amongst PGCE graduates, with fewer very high earners than among masters graduates and undergraduates but also fewer individuals with very low earnings. For all education groups, earnings growth during women's 30s

is modest, with only PhD graduates seeing significant earnings growth when individuals are in their late 30s. While these figures condition on being in employment, we do not observe working hours in the data, and hence any differences in earnings can be due to both differences in wages and differences in hours. The lack of earnings growth for women in their 30s might hence be partially driven by a reduction in working hours as these women start having children.

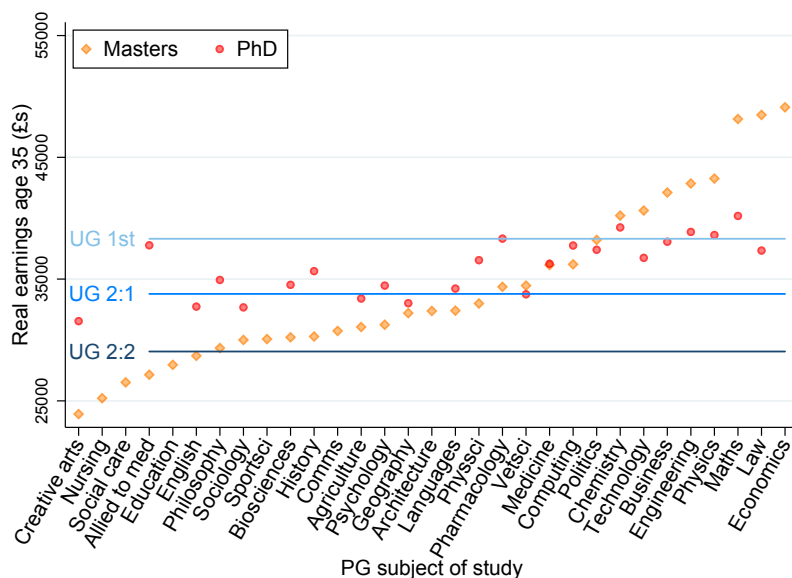
Men see much stronger earnings growth all through their 30s, for all groups. As for women, PGCE graduates have the lowest earnings growth over this period. Unlike for women, PhD graduates have lower average earnings than masters graduates for much of the period observed, possibly due to those individuals having less work experience, but perhaps also because PhD students choose careers that are not so well paid. For men, average PGCE earnings look particularly bad: they are almost £6,000 lower than for undergraduates at age 30 and over £20,000 lower at 40. This might explain the lower number of men choosing to take this route. As with women, however, the difference nearly disappears when we compare median earnings of the two groups.

While Figure 6 shows that, on average, individuals with a masters degree or a PhD earn more by age 35 than those with only an undergraduate degree, this is not true for all courses. Figure 7 shows average earnings for women at age 35 by masters and PhD subject, and compares them with the earnings of those with only an undergraduate degree, by degree classification (averaged across all undergraduate subjects). As we saw earlier, masters and PhD graduates are more likely to have received a first or 2:1 than those who did not do a postgraduate course, so average earnings of those students might provide the most relevant benchmark. The equivalent figures showing median rather than mean earnings are shown in Appendix Figure A4 .

Women with a masters degree in LEM and STEM subjects have the highest average earnings. For example, women with a masters in economics, law or maths earn around £50,000 on average at age 35, around £10,000 more than the average undergraduate with a first-class degree (but no postgraduate qualifications). While there are a few additional masters subjects where average earnings exceed those of the average undergraduate with a first-class degree (including business, engineering and physics), there are also a handful of masters subjects – including creative arts and nursing – that actually have lower mean earnings than the average undergraduate who received a 2:2 and did not progress to achieve a postgraduate qualification. For PhDs, the differences across subjects are less stark; average earnings for most PhD subjects are similar to or higher than those of the average undergraduate with a 2:1, and the gap between the top subject (maths) and the

bottom subject (creative arts) is less than £10,000, compared with an equivalent figure of more than £25,000 for masters degree subjects (where the top subject is economics).

Figure 7: Average earnings for those in work at age 35 by postgraduate subject of study (women)



Note: Highest qualification is as defined in Section 2.2. The sample is based on all individuals in column 6 of Table 1 who are in sustained employment and have positive earnings. Degree subjects where we observe fewer than 30 graduates with valid earnings observations at age 35 are excluded. The figure includes PAYE and SA earnings, pooling across years where we observe both of these (2013/14 to 2016/17). UG averages by degree classification exclude those who go on to PG study. All earnings are in 2018/19 prices.

Figure 8 shows the equivalent numbers for men.<sup>18</sup> The ranking of masters subject by average earnings is very similar to that for women, with economics, law and maths at the top end and education, nursing, creative arts and social care at the bottom. However, the scale is rather different, with average earnings for students with a masters in economics exceeding £85,000 at age 35, compared with just over £30,000 for social care. For men, fewer masters subjects have average earnings above those of undergraduates with a first, and more subjects have average earnings below those of undergraduates with a 2:2, than is the case for women.

Interestingly, the pattern for PhD subjects is quite different for men from what it is for women. We saw above that there is not a huge amount of variation across subjects for women, but there is for men. Average earnings of those with PhDs in architecture or creative arts are around £35,000 – considerably below average earnings of undergraduates with a 2:2 – while the average for those with a PhD in economics is more than £80,000 by age 35 – around £10,000 more than the average

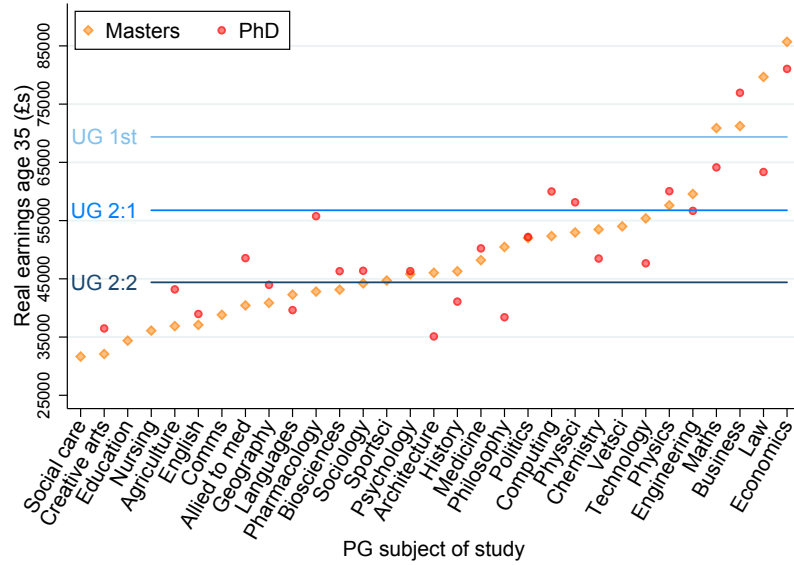
<sup>18</sup>The equivalent figure showing median rather than mean earnings is shown in Appendix Figure A4 .

undergraduate with a first-class degree.

Appendix Figure A5 shows how earnings of masters graduates vary by undergraduate subject and by whether the masters taken was in a similar subject to the undergraduate degree. We see that there are many subjects where graduates who took a masters in a different subject from their undergraduate degree actually have higher average earnings than graduates who took a masters in the same subject.

In Appendix Figure A6, we further show how, for each undergraduate subject, earnings of PGCE graduates compare with the earnings of those who left education after their undergraduate degree. While some differences in average PGCE earnings exist across individuals who studied different subjects for their undergraduate degree, these differences are very small. Hence, PGCE earnings compare quite well with undergraduate earnings for some of the lower-earning subjects but are much lower than undergraduate earnings for many of the higher-earning subjects.

Figure 8: Average earnings for those in work at age 35 by postgraduate subject of study (men)

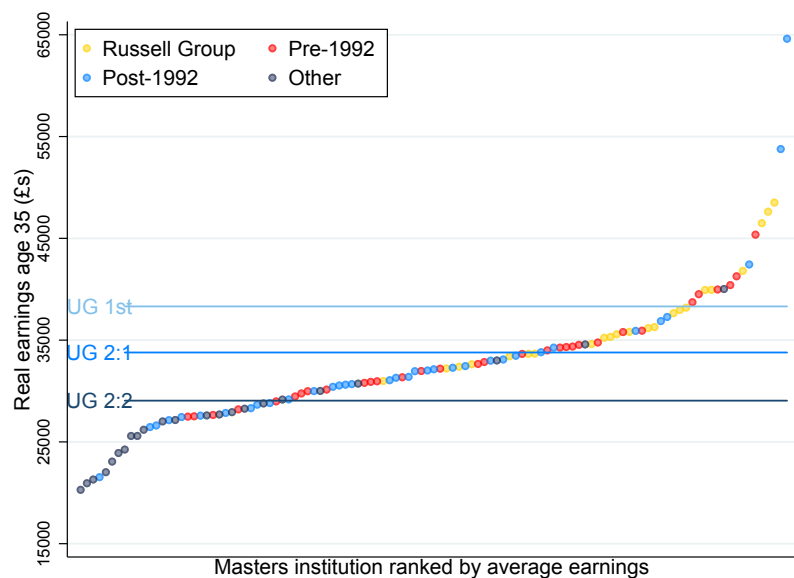


Note: Highest qualification is as defined in Section 2.2. The sample is based on all individuals in column 6 of Table 1 who are in sustained employment and have positive earnings. Degree subjects where we observe fewer than 30 graduates with valid earnings observations at age 35 are excluded. The figure includes PAYE and SA earnings, pooling across years where we observe both of these (2013/14 to 2016/17). UG averages by degree classification exclude those who go on to PG study. All earnings are in 2018/19 prices.

Not only do graduates' earnings vary by subject studied; there are also considerable earnings differences by the institution at which the individual studies. Figure 9 shows this for women. As for undergraduate universities (Belfield et al., 2018a), masters graduates from Russell Group univer-

sities tend to have the highest average earnings, and those from post-1992 and ‘other’ universities have the lowest average earnings. The two universities with the highest average earnings for female masters graduates – Nottingham Trent and Oxford Brookes – are remarkable exceptions to this, being both post-1992 universities. The very high average earnings of these universities are driven to a large extent by the variation in subjects offered at masters level. More than 80% of masters students at Nottingham Trent and nearly half at Oxford Brookes study law, one of the subjects with the highest average earnings. Among the universities with the lowest earnings, we see similar subject specialisation. Many of these institutions are specialist music and arts schools, where virtually all students study creative arts courses, which have very low average earnings. Patterns for men are very similar to those among women, and can be seen in more detail in Appendix Figure A7 . Graduates of London Business School and Nottingham Trent have the highest mean earnings, while those from arts schools tend to have the lowest average earnings.

Figure 9: Average earnings for those in work at age 35 by masters institution (women)



Note: Masters is as defined in Section 2.2. The sample is based on all individuals in column 6 of Table 1 who are in sustained employment and have positive earnings. Institutions where we observe fewer than 30 graduates with valid earnings observations at age 35 are excluded. The figure includes PAYE and SA earnings, pooling across years where we observe both of these (2013/14 to 2016/17). UG averages by degree classification exclude those who go on to PG study. All earnings are in 2018/19 prices.

Equivalent figures for PGCE and PhD institutions are shown in Appendix Figures A8 and A9 . While, on average, graduates of PGCE courses at Russell Group and pre-1992 universities have slightly higher earnings than those from PGCE courses at post-1992 and ‘other’ universities, the



differences are much less stark than for masters courses. The vast majority of PhD students study at Russell Group and pre-1992 universities; hence for most post-1992 and ‘other’ universities, we do not have enough observations to show average earnings for their PhD graduates.

## 4 Methodology

Since having an undergraduate-level qualification is a near-universal prerequisite for entering any postgraduate-level qualification, we estimate the return to postgraduate qualifications *relative to only having an undergraduate qualification*. Nevertheless, of those who have an undergraduate qualification, the students who continue and do a postgraduate degree are still a selected group. As we saw in the previous sections, they did better on average in their undergraduate degrees and are more likely to come from wealthier backgrounds (with the exception of PGCE students). Further, when we consider heterogeneity in returns to different postgraduate courses, it is important to take into account the fact that some courses are much more selective than others, and will therefore accept students that have, on average, graduated from higher-ranked universities and with a higher degree class. Admission onto postgraduate courses also very commonly requires prior qualifications that are relevant to that subject (for example, to do a masters degree in economics, people will typically require an undergraduate qualification in economics or mathematics). All of this means that while the average earnings comparisons shown in the previous section are interesting, they do not necessarily tell us about how much a specific postgraduate degree is likely to increase earnings by, conditional on having the option to do it. In order to estimate this, we have to control for the above differences between students.

We do this using ordinary least squares (OLS) estimation. To understand the basic premise of our approach, consider equation 1:

$$\ln(y_{it}) = \alpha + Masters_i\beta + PhD_i\delta + PGCE_i\rho + X_i'\gamma + \epsilon_{it} \quad (1)$$

Here  $\ln(y_{it})$  are log earnings of individual  $i$ ,  $Masters_i$ ,  $PhD_i$  and  $PGCE_i$  are indicators for whether the highest qualification individual  $i$  obtained by age 30 is a masters, PhD or PGCE respectively.<sup>19</sup>

The set of individual controls  $X_i$  includes:

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<sup>19</sup>This specification means that the return to PhD degrees *includes* the return to any previous postgraduate qualifications the individual has obtained. This decision was based on the routes people take to a PhD highlighted in Table 3. In fact, more than half of people who get PhD degrees jump straight to PhD level from their undergraduate degree, without taking some kind of intermediate qualification (such as a masters) first.

- tax year of earnings;
- year graduated from undergraduate degree;
- age started undergraduate degree;
- POLAR quintile;
- ethnicity;
- region of domicile when applying for university;
- degree class, subject(s) and institution of undergraduate degree.

Unlike in our previous work looking at the returns to undergraduate degrees (Belfield et al., 2018a), we here do not control for school attainment. The oldest cohort for whom the data are linked to school records through the NPD is aged 30 in 2016/17, the last year of our data. As individuals often are in their mid-to-late 20s when finishing their postgraduate course (see Appendix Figure A2 for a summary of the age individuals in our sample *started* each course), estimating the returns at this age – when many will only have just entered the labour market – would not be representative of the returns to these courses. We instead use additional birth cohorts for which we have HESA data, but no school records, which allows us to include individuals up to age 40 in the analysis. While we cannot control for school attainment for these individuals, we can control for their detailed undergraduate attainment, which is likely to capture the differences in prior attainment and ability that are relevant for earnings. In Section 5.1, we check the validity of this assumption by comparing returns with and without the school records for the 2002 GCSE cohort, for which we observe complete school and university records, as well as earnings data up to age 30.

While we show how overall returns to the different postgraduate qualifications evolve across ages in Section 5.1, our main results focus on the return at age 35. We chose this age for our headline results as we believe this is the oldest age at which we can show robust and reliable returns. While we have data for earlier cohorts that would allow us to estimate returns up to age 40, the resulting estimates would be less reliable for four reasons. First, our sample size would be much reduced, as we would be able to rely only on one birth cohort. Second, the quality of HESA data is lower for earlier cohorts. Most importantly, subject studied is unknown for around 10% of first-degree students leaving university before 2003. Third, match rates to HMRC data are low for the earliest cohorts, reducing our sample size further and introducing possible bias. About a third

of students graduating in 1996 can never be matched to an HMRC record, compared with 12% of those graduating in 2003 and less than 5% of those graduating in 2013. Fourth, the information we have on students' ages is less reliable for the earliest cohorts, again leading to potential bias.<sup>20</sup> However, our finding in Section 5.1 that the results evolve fairly smoothly across ages reassures us that the later data are still telling us something meaningful about the returns, which justifies our inclusion of those data in the panel model described below.

We follow our previous work and focus the estimation on those with positive earnings and in sustained employment<sup>21</sup> and include earnings observations in a pooled cross-sectional model. We include earnings from *both* employment (from Pay As You Earn (PAYE) records) and self-employment (from Self Assessment (SA) records) for the 2013/14 to 2016/17 tax years. Using earlier tax years, while increasing our sample size, would mean we are not able to include self-employment income as we do not have access to the SA records prior to 2013/14. By age 35, providing estimates of earnings returns without including self-employment income would potentially be misleading, as this component of income is becoming increasingly important as individuals age: more than 10% of individuals in our sample have some self-employment income at age 35. Using these years has the additional advantage of being more recent, and also leaves some time for earnings to recover from the 2008 recession. We include earnings from ages 33 to 40 in the estimation and model returns by using a quadratic time trend within this age range. We exclude earnings observations before age 33 as earnings in the first few years after graduation are noisy and possibly uninformative about the long-run returns from a degree.

The pooled cross-sectional model that we use extends the very simple model given in equation 1 to include multiple earnings observations per individual, thereby increasing the precision of our estimates. We estimate the following equations for the overall, subject and institution returns respectively:

$$\begin{aligned}
\ln(y_{it}) = & \alpha + \omega_1 t + \omega_2 t^2 + Masters' \beta_0 + (Masters * t)' \beta_1 + (Masters * t^2)' \beta_2 \\
& + PhD' \delta_0 + (PhD * t)' \delta_1 + (PhD * t^2)' \delta_2 \\
& + PGCE \rho_0 + (PGCE * t) \rho_1 + (PGCE * t^2) \rho_2 \\
& + X_i' \gamma + \epsilon_{it}
\end{aligned} \tag{2}$$

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<sup>20</sup>The reason is that we only directly observe the age at which students started their course, but we do not have data on the whole of students' university careers for the earliest cohorts.

<sup>21</sup>Defined as working five out of the last six months of the tax year.

$$\begin{aligned}
\ln(y_{it}) = & \alpha + \omega_1 t + \omega_2 t^2 + \text{MastersSubj}'\beta_0 + (\text{MastersSubj} * t)'\beta_1 + (\text{MastersSubj} * t^2)'\beta_2 \\
& + \text{PhDSubj}'\delta_0 + (\text{PhDSubj} * t)'\delta_1 + (\text{PhDSubj} * t^2)'\delta_2 \\
& + \text{PGCE}\rho_0 + (\text{PGCE} * t)\rho_1 + (\text{PGCE} * t^2)\rho_2 \\
& + X_i'\gamma + \epsilon_{it}
\end{aligned} \tag{3}$$

$$\begin{aligned}
\ln(y_{it}) = & \alpha + \omega_1 t + \omega_2 t^2 + \text{MastersHEI}'\beta_0 + (\text{MastersHEI} * t)'\beta_1 + (\text{MastersHEI} * t^2)'\beta_2 \\
& + \text{PhDHEI}'\delta_0 + (\text{PhDHEI} * t)'\delta_1 + (\text{PhDHEI} * t^2)'\delta_2 \\
& + \text{PGCEHEI}'\rho_0 + (\text{PGCEHEI} * t)'\rho_1 + (\text{PGCEHEI} * t^2)'\rho_2 \\
& + X_i'\gamma + \epsilon_{it}
\end{aligned} \tag{4}$$

Here all variables are as in equation 1, except we introduce  $t$ , which is time relative to age 35. All regressions are run separately for men and women. As in Belfield et al. (2018a), institution estimates represent the average return at the institution, given the set of subjects they offered. At postgraduate level, there is significant specialisation in different subjects across institutions, which implies we may compare people who studied different subjects when comparing institutions.<sup>22</sup>

Given the smaller number of individuals studying postgraduate courses, we are not able to provide estimates of the returns at the ‘course’ (i.e. subject-institution) level as we did for undergraduate degrees in Belfield et al. (2018a), and instead only show returns by institution and subjects separately. We do, however, show heterogeneity in returns by subject studied at undergraduate level for PGCEs and masters degrees. These estimates might be the most relevant for individuals choosing whether to proceed to postgraduate study, as they show them the average returns to different masters degree subjects for people with the same undergraduate qualification as themselves. Unfortunately, estimating returns separately for each masters subject given each undergraduate subject is too demanding given our sample sizes. In Section 6.3, we therefore estimate, for each undergraduate subject, the returns to a masters degree in the same subject, a similar subject (within the same subject group<sup>23</sup>) or an entirely different subject.

In addition to knowing the impact of postgraduate qualifications on average earnings, it is informative to understand the impact of a postgraduate qualification on the probability of achieving

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<sup>22</sup>This is unavoidable as we cannot control directly for subject studied at postgraduate level, as the control group – not doing a postgraduate course – is perfectly collinear for each set. A similar point applies for the subject model: we do not control for the institution attended when looking at the average subject returns.

<sup>23</sup>Subject groups are defined as science, technology, engineering and maths (STEM), law, economics and management (LEM) and arts, other social sciences and humanities (other) which contains all remaining subjects. A detailed list of the subjects included in each of these categories is included in the online appendix.

a certain income level. This does not always relate directly to the impact on average earnings, due to differences in earnings inequality across qualification levels. For example, we saw in Figure 6 that the earnings of PGCE graduates look much better relative to the other qualifications when we looked at median rather than mean earnings, which is due to PGCE graduates having a very compressed earnings distribution. While a PGCE might not provide very high returns in terms of average earnings, graduates might still find a PGCE attractive if it offers some insurance against very bad earnings outcomes. Hence, while our main results focus on the effects of postgraduate qualifications on average earnings, we will also show the impact these qualifications have on the probability of being in sustained employment, and also on the probability of earning more than £20,000, £30,000, £40,000 and £50,000.

To estimate this, we use a linear probability model (LPM) as follows:

$$E_i = \alpha + Masters_i\beta + PhD_i\delta + PGCE_i\rho + X_i'\gamma + \epsilon_{it} \quad (5)$$

where  $E_i$  is a dummy variable that is equal to 1 if the individual is in sustained employment (or, alternatively, earning more than £20,000, £30,000, £40,000 or £50,000) and 0 otherwise. The control variables are as in the rest of the analysis. As this is a linear probability model, we do not include a panel model as above, and instead only use observations at age 35. In order to estimate the impact on the probability of being in sustained employment, we additionally need to include in our sample the individuals who are not in sustained employment, and hence our sample for this part of the analysis will include all individuals in column 5 of Table 1 whom we observe at age 35.

## 5 Overall returns to postgraduate degrees

We start by estimating the average impact of having a PGCE, masters or PhD at age 35 compared with only having an undergraduate degree. The results are shown in Table 6. The top panel shows the estimates for women and the bottom one for men. As described in the previous section, the results for men and women are from separate regressions, while the estimates for PGCE, masters and PhD come from the same regression model.

Columns 1–5 show how the results change with the sequential addition of control variables. We start in column 1 by showing the raw differences in earnings from a regression model without including any background or prior attainment controls, hence including controls for year of graduation,

tax year of earnings and the age the individual started their undergraduate degree only. We saw in the descriptive plots in Figure 6 that individuals with masters or PhD degrees earn significantly more than those with only an undergraduate qualification at age 35, while PGCE graduates earn less. This result is replicated here: for women, PGCE graduates earn around 3% less than those with only an undergraduate degree, while masters graduates earn 7% more and PhD graduates earn 19% more. For men, PGCE graduates earn 9% less than undergraduates, while masters and PhD graduates earn 7% and 9% more, respectively.<sup>24</sup>

Subsequent columns in Table 6 show how these estimates change once we account for differences in background and undergraduate attainment. Including background characteristics does very little to alter any of the estimates of returns, but controlling for undergraduate degree class, subject and institution all significantly reduce the returns to masters and PhD courses. The direction of this effect is as expected, but the magnitude is perhaps surprising. For women, masters degrees increase earnings by just 1.5% at age 35 (down from 7% in raw terms), while PhDs increase earnings by 8% (down from 19% in raw terms). For men, the results are even starker, and suggest that masters and PhD degrees actually *reduce* earnings at age 35, by 2.3% and 9% respectively.

For PGCEs, we see the opposite pattern: controlling for undergraduate degree subject *increases* the returns to a PGCE, driven by PGCE graduates on average having studied less high-earning subjects than the typical undergraduate graduate. The final estimated earnings returns to PGCEs remain low for both genders, at 1.2% for women and -2.5% for men, although both numbers are statistically significantly different from zero.

When comparing the returns across genders, it needs to be kept in mind that these estimates show the return in terms of *earnings*, and hence include both any impact on wages and any impact on hours worked. While we cannot observe hours in our data, we would expect female hours to vary more by education level than male hours, thereby potentially driving the higher returns for women than for men.

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<sup>24</sup>These percentage estimates will not align exactly with the raw differences observed in Figure 6 both because of the ‘age started undergraduate degree’ controls and because they come out of the pooled panel model described in the previous section.

Table 6: Average returns to postgraduate degrees at age 35, by qualification type

	(1)	(2)	(3)	(4)	(5)
<i>Women</i>					
PGCE	-0.031*** (0.003)	-0.022*** (0.003)	-0.021*** (0.003)	0.013*** (0.003)	0.012*** (0.003)
Masters	0.072*** (0.003)	0.069*** (0.003)	0.056*** (0.003)	0.030*** (0.003)	0.015*** (0.003)
PhD	0.170*** (0.005)	0.172*** (0.005)	0.126*** (0.005)	0.109*** (0.006)	0.075*** (0.006)
N	1,291,614	1,291,614	1,291,614	1,291,614	1,291,614
<i>Men</i>					
PGCE	-0.090*** (0.003)	-0.070*** (0.003)	-0.074*** (0.003)	-0.029*** (0.003)	-0.025*** (0.003)
Masters	0.070*** (0.003)	0.071*** (0.003)	0.023*** (0.003)	0.009*** (0.003)	-0.023*** (0.003)
PhD	0.086*** (0.004)	0.088*** (0.004)	-0.034*** (0.004)	-0.049*** (0.004)	-0.094*** (0.004)
N	1,579,701	1,579,701	1,579,701	1,579,701	1,579,701
Age & year	✓	✓	✓	✓	✓
Background		✓	✓	✓	✓
UG degree class			✓	✓	✓
UG subject				✓	✓
UG university					✓

Standard errors are given in parentheses.

\*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Note: The sample is based on column 6 of Table 1. Figures show the coefficients on having a PGCE, masters or PhD as highest qualification. Age and year controls include tax year of earnings, year graduated from the undergraduate degree and the age started undergraduate degree. Returns are given in log-points. Background controls include controls for ethnicity, POLAR quintile of area of residence when applying for university and region of domicile when applying for university.

## 5.1 Specification checks

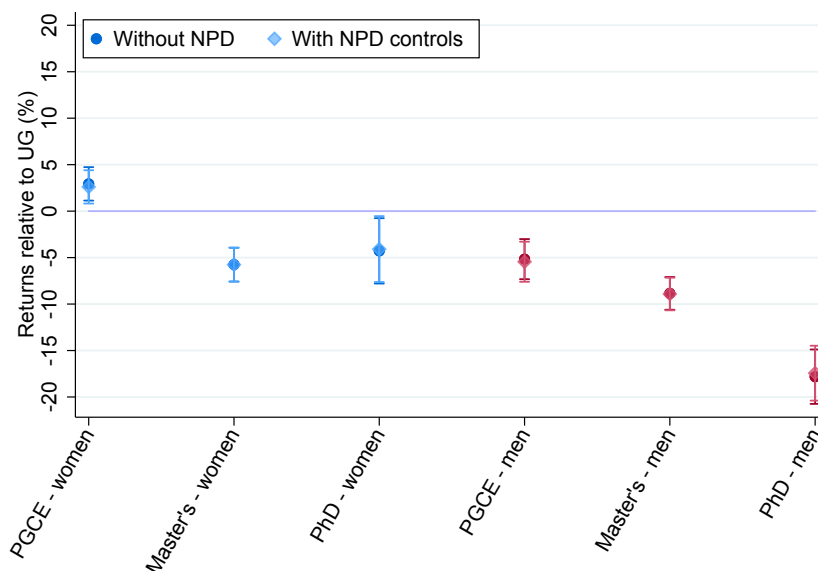
### 5.1.1 Controls for school attainment

There are two main potential concerns about the results in the previous section, which we address in turn here. First, all of our conditioning variables are based on university records obtained from HESA data, meaning that we do not include any information on attainment prior to entering university. In doing this, we are implicitly assuming that prior attainment has no effect on earnings

other than through its effect on university attainment.<sup>25</sup> We are able to check the validity of this assumption by estimating returns with and without controlling for school attainment using a cohort for which we have school records, university records and tax records.

To do this, we make use of the 2002 GCSE cohort, which is the oldest cohort for which we have school, university and tax records and for which we can observe earnings up to age 30. In Figure 10, we compare the returns to postgraduate qualifications at age 30 for this cohort when we estimate them using our main specification, and when we additionally control for attainment at KS4 and KS5 (ages 16 and 18).<sup>26</sup> We can see that these additional controls indeed have very little impact on our estimates of returns.

Figure 10: Robustness to including NPD controls – overall postgraduate returns at age 30



Note: Sample is the 2002 GCSE cohort, using the earnings observation from the 2016/17 tax year when these individuals are approximately 30 years old. Additional NPD controls include UCAS tariff score, dummies for having a maths, science and social science A level, number of A\*, A, B and C grades at GCSE level and KS4 points score. The bars represent the 95% confidence intervals.

In Appendix Figures A10 and A11, we go a step further than this and test the impact of excluding school attainment controls for the returns by masters subject. Even in that case, the estimated returns are very similar. For the subjects with the highest returns, the inclusion of the extra attainment measures reduces the point estimates of returns a little, but this difference is not

<sup>25</sup>More explicitly, through its effect on the specific university attended, the subject studied and the degree class obtained.

<sup>26</sup>As we only have the NPD records for individuals who went to school in England, in this exercise we are restricted to looking at the returns for English students, so it is therefore not entirely comparable to the main results, which look at UK students.



statistically significant. We conclude from this exercise that excluding controls for attainment prior to entering university does not seem to result in significant bias in our headline estimates. When it comes to more refined estimates, such as by subject or institution, it is possible that the exclusion of these controls may create a small upward bias in some of our estimates that should be kept in mind. Overall we find the results from this test to be reassuring for our results.

### 5.1.2 Quadratic time trend

We now consider the choice of using a pooled panel data model with a quadratic trend in age. In Figures 11, 12 and 13, we show results from separate regression models run at each age.<sup>27</sup> We observe that the results at age 35 are extremely similar to the headline estimates in the final column of Table 6, and that the pattern in returns over time can be well approximated by a quadratic, both of which are reassuring for our approach of using a quadratic specification in our panel data model for our main results in Table 6 and in the following sections. As described in the methodology section, we have a preference for such an approach as it makes use of more of the data, smoothing across several cohorts and thereby increasing the precision of our estimates. This is particularly useful when estimating the returns for sub-populations, such as by masters subject or institution, which for some of the smaller courses may otherwise rely on very small samples.

Figures 11, 12 and 13 are additionally informative in that they tell us something about how the returns to different postgraduate degrees evolve with age.<sup>28</sup> In line with the low earnings growth among PGCE graduates that we saw in Figure 6, average PGCE returns are mostly decreasing during the 30s, and flattening out towards the end of this period. Returns to masters degrees initially increase slightly but remain small and positive for women, and small and negative for men throughout their 30s. This suggests that the returns we present at age 35 for masters degrees are not masking a sharp positive trend in returns. Conversely, PhD returns are increasing over time for both men and women. Women with PhD degrees experience average returns of almost 20% at age 40, up from around zero at age 30 and around 10% at 35. For men, there is a similar increase but starting from a lower baseline: returns are close to zero at age 40, having been -14% at 30 and -9% at 35. This positive trend is likely to reflect the strong positive returns to the first few years of work experience, which for many PhD graduates will be much later than for those who started

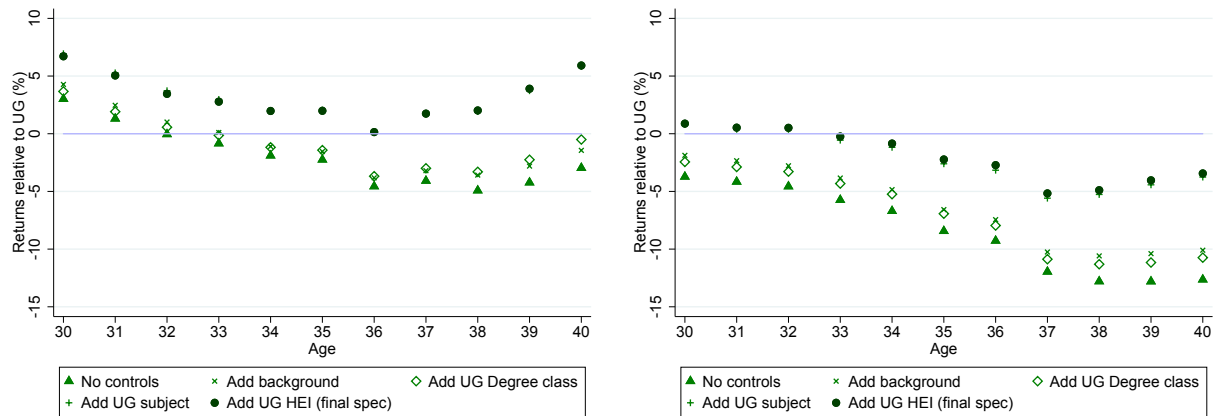
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<sup>27</sup>We here show how returns evolve throughout the 30s, but our main model only includes observations from age 33 onwards.

<sup>28</sup>Some of these single-age results should be interpreted with caution, especially for the estimates of returns in the late 30s, as those estimates will rely on a limited number of individuals and cohorts only.

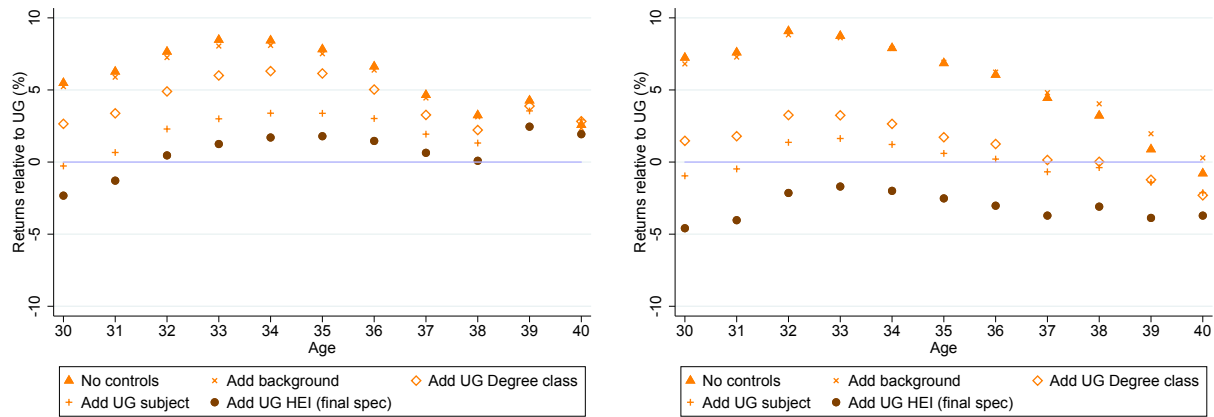
work straight after their undergraduate degree.

Figure 11: Returns to PGCE degrees by age (women left, men right)



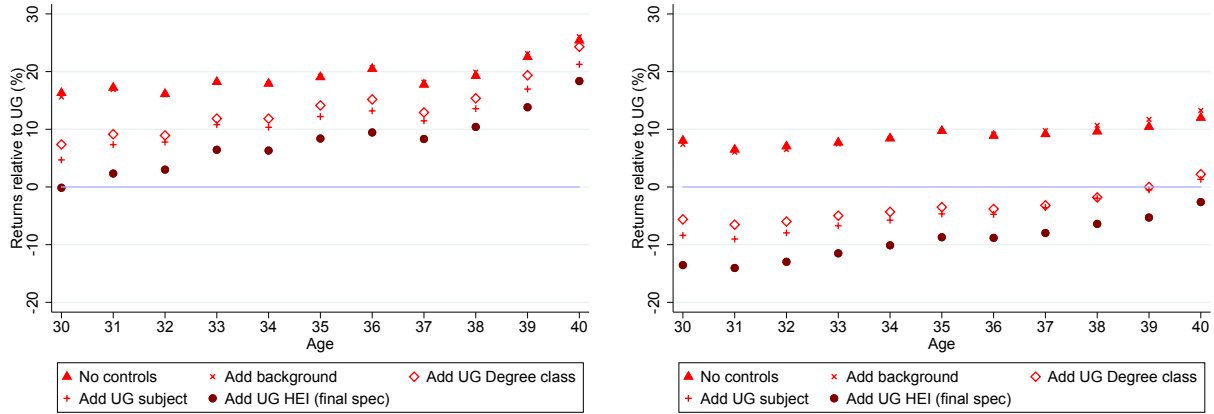
Note: Figures show the coefficients on PGCE degrees from a regression where we successively add controls. The coefficients at each age come from a separate regression including only earnings observations at the indicated age. Figures have been put into percentage points.

Figure 12: Returns to masters degrees by age (women left, men right)



Note: Figures show the coefficients on masters degrees from a regression where we successively add controls. The coefficients at each age come from a separate regression including only earnings observations at the indicated age. Figures have been put into percentage points.

Figure 13: Returns to PhD degrees by age (women left, men right)



Note: Figures show coefficients on PhDs from a regression where we successively add controls. The coefficients at each age come from a separate regression including only earnings observations at the indicated age. Figures have been put into percentage points.

## 5.2 Effect on the distribution of earnings

To give a more complete picture of the overall labour market impact of postgraduate degrees, in Table 7 we further estimate the impact of the probability of being in sustained employment and, subsequently, the probability of earning above various thresholds. In all the columns, we include the full set of controls, as in column 5 of Table 6. For these estimates, we necessarily include the full population of graduates with a linked HMRC record (including those not in sustained employment), and focus on age 35 only.

Table 7: Impact on being in sustained employment and on earning above various thresholds for postgraduate degrees at age 35, by qualification type

	(1) Sustained employment	(2) Earnings > £20k	(3) Earnings > £30k	(4) Earnings > £40k	(5) Earnings > £50k
	(1)	(2)	(3)	(4)	(5)
<i>Women</i>					
PGCE	0.025*** (0.002)	0.058*** (0.003)	0.066*** (0.003)	-0.018*** (0.003)	-0.078*** (0.001)
Masters	0.008*** (0.002)	0.027*** (0.003)	0.020*** (0.003)	0.000 (0.003)	-0.012*** (0.002)
PhD	0.009* (0.005)	0.098*** (0.006)	0.093*** (0.007)	0.018*** (0.006)	-0.067*** (0.004)
N	263,074	263,074	263,074	263,074	263,074
<i>Men</i>					
PGCE	0.022*** (0.003)	0.097*** (0.004)	0.150*** (0.004)	-0.005 (0.004)	-0.164*** (0.003)
Masters	-0.011*** (0.002)	-0.010*** (0.003)	-0.005* (0.003)	-0.016*** (0.003)	-0.025*** (0.002)
PhD	-0.018*** (0.004)	0.039*** (0.005)	0.052*** (0.005)	-0.037*** (0.006)	-0.142*** (0.005)
N	289,722	289,722	289,722	289,722	289,722
Age start UG & tax year	✓	✓	✓	✓	✓
Background	✓	✓	✓	✓	✓
UG degree class	✓	✓	✓	✓	✓
UG subject	✓	✓	✓	✓	✓
UG university	✓	✓	✓	✓	✓

Standard errors are given in parentheses.

\*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Note: Figures show the coefficients on having a PGCE, masters or PhD as highest qualification from a linear probability model on dummies for being in sustained employment, earning more than £20,000, more than £30,000, more than £40,000 and more than £50,000 at age 35. We do not here restrict on being in sustained employment or having positive earnings. The sample is equivalent to all observations at age 35 of individuals included in column 5 of Table 1.

In column 1, we show the estimated effect on the probability of being in sustained employment, while in columns 2–5 we estimate the effect on the probability of earning more than £20,000, £30,000, £40,000 and £50,000 respectively at age 35. The results suggest that achieving a PGCE degree increases the chances of being in sustained employment, and also increases the chances of earning above £20,000 and £30,000. For women, it increases the latter by 6.6ppts, while for men it

increases it by a quite dramatic 15ppts. However, PGCEs actually *decrease* the chances of earning more than £40,000 by a small amount and decrease the chances of earning more than £50,000 substantially (by 8ppts for women and 16ppts for men). This suggests that PGCEs are a relatively ‘safe’ choice for both women and men: they reduce the chances of low earnings but also reduce the chances of achieving high earnings. This finding aligns with our descriptive result from Figure 6, which showed that median earnings of PGCE graduates and undergraduates are very close, yet PGCE graduates’ mean earnings are much lower.

Perhaps surprisingly, we mostly see quite similar patterns for PhD degrees, which also reduce the chance of low earnings but reduce the chances of very high earnings. Perhaps this is because, like PGCEs, PhDs tend to result in people pursuing specific interests – such as working in a research environment – that are not necessarily the most lucrative. For women, we see this same pattern for masters degrees. For men, however, masters degrees on average reduce the probability of earning above each of the shown thresholds by a very small amount (typically around 1ppt).<sup>29</sup>

## 6 Heterogeneity in returns to masters and PhD degrees

In this section, we go beyond the average overall returns outlined in the previous section and investigate how the returns to masters and PhD degrees vary by subject studied and institution attended. We then look at variation in returns depending on *undergraduate* degree subject. We consider heterogeneity in returns to PGCE degrees in Section 7.

### 6.1 Returns by *postgraduate* subject

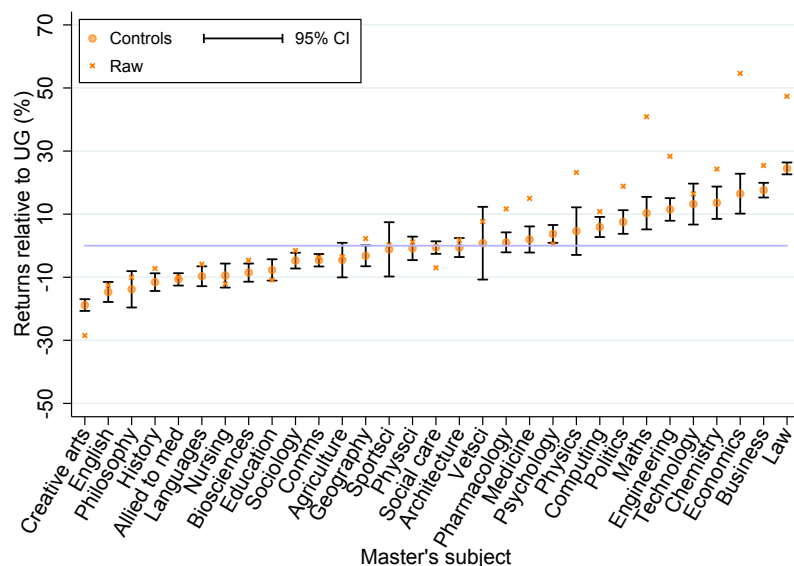
We start in Figure 14 by showing our estimated returns to different masters subjects for women. The figure shows both the estimated returns (the equivalent to column 5 of Table 6) and their confidence intervals, and the raw differences (the equivalent to column 1 of Table 6). We see that, in the majority of cases, the controls act to reduce our estimates of the returns, although this is much more extreme amongst the higher-returning subjects, suggesting these subjects attract individuals with particularly high earnings potential. In terms of returns, while the *overall* returns to a masters for women are positive, we estimate that only around a third of of masters subjects

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<sup>29</sup>Overall we get extremely similar results when we re-estimate columns 2–5 using only those in sustained employment, suggesting that the inclusion of those not in employment does not drive the results in most cases. However, the estimates of the probability of earning more than £20,000 and £30,000 for men with masters degrees are zero in these specifications, meaning the (small) negative estimates shown here are driven by those not in sustained employment.

have statistically significant positive returns. STEM and LEM subjects have the highest returns on average, with business, economics and law increasing earnings by 15% or more. On the other hand, masters degrees in arts and humanities mostly see negative returns, with creative arts and English having the lowest average returns at around -19% and -15% respectively.

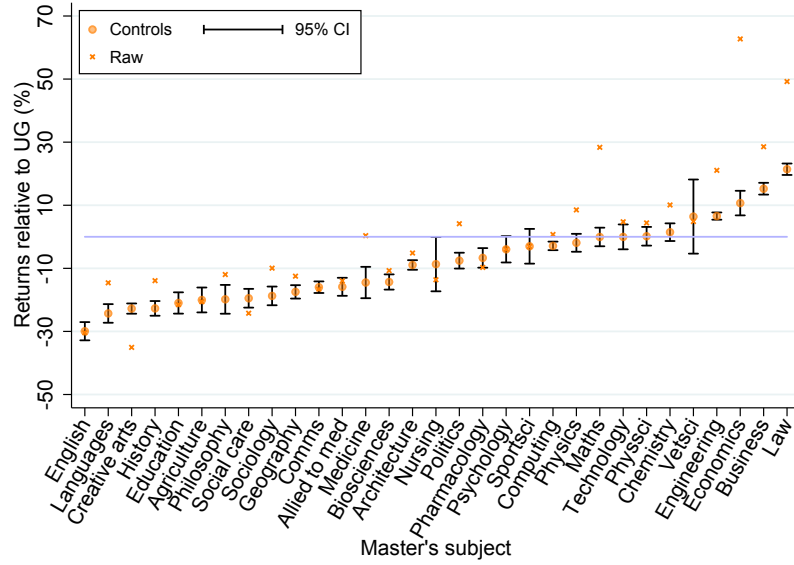
Figure 14: Returns to masters degrees at age 35, by masters subject (women)



Note: Figure reports estimates of the impact of studying different masters subjects on annual earnings at age 35, conditional on being in sustained employment, controlling for age, background and prior attainment. Raw earnings differences are shown with a cross alongside the estimates of returns. Results have been converted to percentage differences using a log-point conversion. Subjects are only included if they have at least 30 earnings observations at age 35.

Figure 15 shows the equivalent for men. In line with the lower overall returns for men, only a few masters subjects have statistically significant positive returns – namely, law, business, economics and engineering – and most subjects have statistically significant negative returns. The ranking of subjects for men is very similar to the ranking for women. On average, masters in the arts and humanities tend to have low earnings returns, with the highest earnings returns for LEM subjects. When interpreting these results, for both figures, it does need to be kept in mind that these subject returns do not adjust for the institutions at which the courses are offered. This implies that if a subject is disproportionally offered by higher-return universities, the impact of higher university quality will be included in the average returns for that subject.

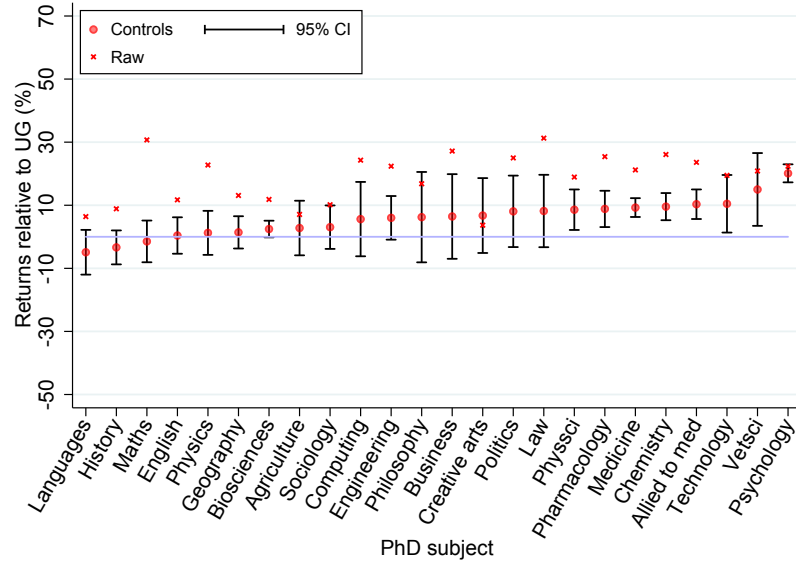
Figure 15: Returns to masters degrees at age 35, by masters subject (men)



Note: Figure reports estimates of the impact of studying different masters subjects on annual earnings at age 35, conditional on being in sustained employment, controlling for age, background and prior attainment. Raw earnings differences are shown with a cross alongside the estimates of returns. Results have been converted to percentage differences using a log-point conversion. Subjects are only included if they have at least 30 earnings observations at age 35. The bars represent the 95% confidence intervals.

Figures 16 and 17 estimate returns by subject for PhD degrees. As would be expected, we can only estimate PhD returns for a smaller set of subjects, since PhD degrees are not very common within some disciplines. Smaller sample sizes within each subject also result in lower precision in our estimates. We see in Figure 16 that while female PhD graduates of all subjects on average have higher earnings than those with only an undergraduate degree (as shown by the raw estimates), once we control for differences in background and attainment these differences are considerably reduced. Many of the estimated returns by subject are not significantly different from zero, with a handful of subjects experiencing significantly positive returns. It is notable here that the ordering of returns is very different from the ordering for masters degrees, which are themselves quite similar to the ordering for undergraduate degrees highlighted in our previous research (Belfield et al., 2018a). For example, psychology is the highest-returning subject (with a return of around 20%), while maths and physics are towards the bottom end. This is likely driven by the different types of occupations that PhDs in different disciplines open up for their graduates.

Figure 16: Returns to PhD degrees at age 35, by PhD subject (women)

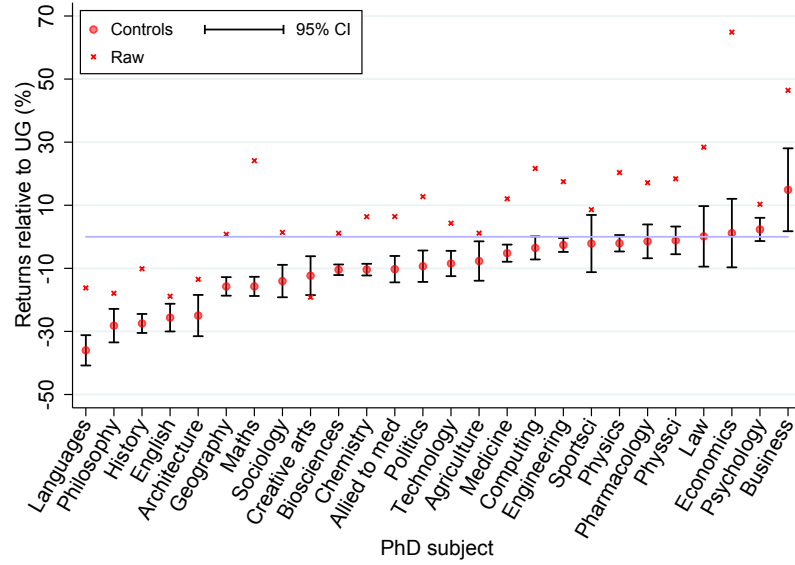


Note: Figure reports estimates of the impact of studying different PhD subjects on annual earnings at age 35, conditional on being in sustained employment, controlling for age, background and prior attainment. Raw earnings differences are shown with a cross alongside the estimates of returns. Results have been converted to percentage differences using a log-point conversion. Subjects are only included if they have at least 30 earnings observations at age 35. The bars represent the 95% confidence intervals.

For men, the picture is less positive, with only one subject – business – having a statistically significantly positive return and more than half of the subjects having significantly negative returns. Returns to PhD degrees are around -25% for architecture and English, and even lower for languages, philosophy and history. The figure highlights the dramatic impact the conditioning variables have on the returns estimates. These differences are largest for maths, which has a raw earnings gap of +24% but a return of less than -15%, and economics which, although it has a raw earnings premium of nearly 65%, has returns of around zero once we account for the high prior attainment of its graduates. When interpreting these results, we need to take into account that returns to PhDs are still increasing after age 35, as we saw in Figure 13; hence PhD returns later in life may look more positive than what we are seeing here. It is also worth mentioning again that we are measuring the returns in terms of earnings, and are, for example, not measuring job quality or satisfaction, which are likely to be important reasons for doing PhD degrees.



Figure 17: Returns to PhD degrees at age 35, by PhD subject (men)



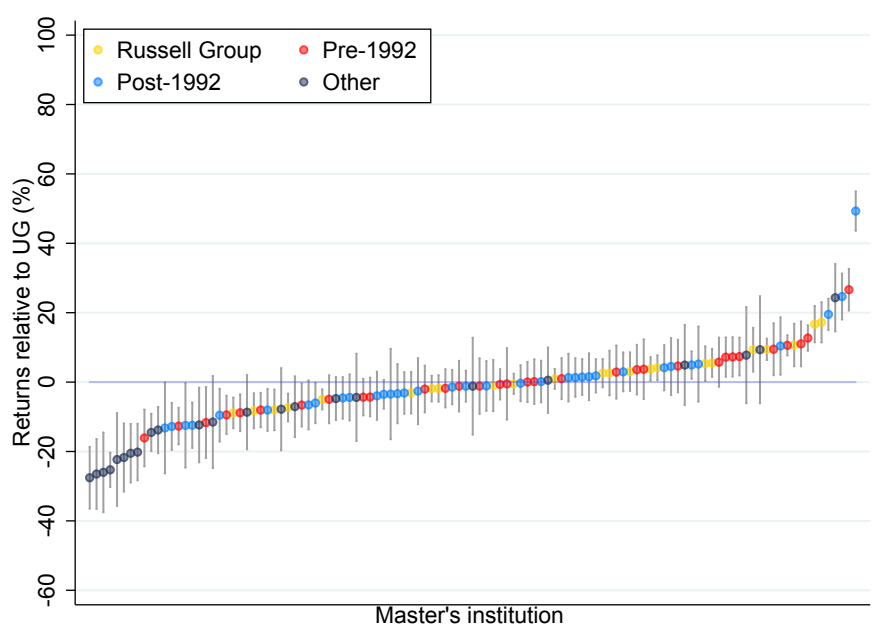
Note: Figure reports estimates of the impact of studying different PhD subjects on annual earnings at age 35, conditional on being in sustained employment, controlling for age, background and prior attainment. Raw earnings differences are shown with a cross alongside the estimates of returns. Results have been converted to percentage differences using a log-point conversion. Subjects are only included if they have at least 30 earnings observations at age 35. The bars represent the 95% confidence intervals.

## 6.2 Returns by *postgraduate* institution

We now turn to comparing the returns to masters degrees at different institutions.<sup>30</sup> Figure 18 shows the return to a masters degree by institution for women, while Figure 19 shows the same for men. Even once we control for differences in undergraduate subject, institution and attainment, the differences in returns are very large. For women, a handful of institutions have returns of -20% or lower. At the other end of the scale, returns to a masters at Nottingham Trent are around 50% for women. For men, the pattern across universities is very similar, although the overall returns are lower and hence fewer institutions have positive returns.

<sup>30</sup>Equivalent estimates for PhD degrees can be found in Appendix Figure A12. As PhD courses tend to be relatively small and concentrated at a small set of universities, we are able to estimate returns for only a small set of institutions, which are typically pre-1992 and Russell Group universities.

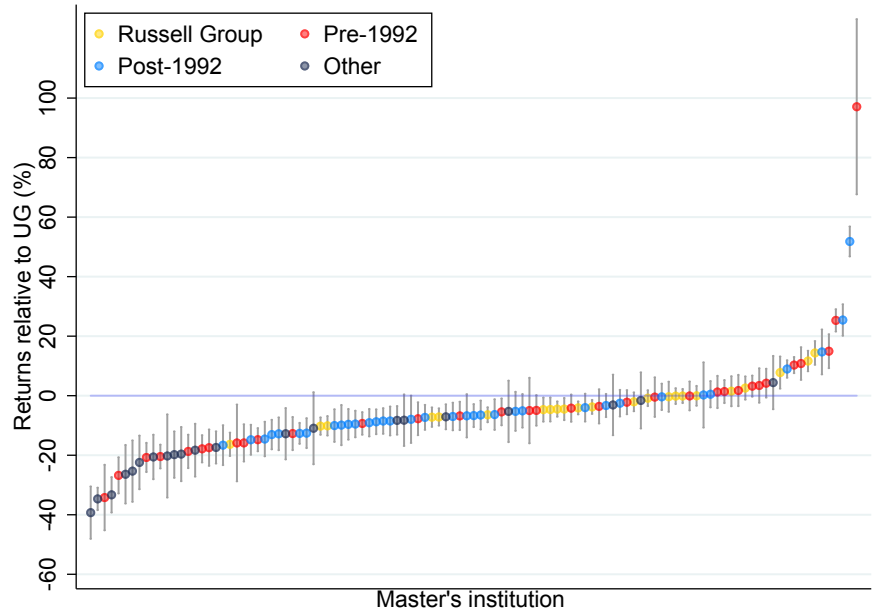
Figure 18: Returns to masters degrees at age 35, by masters institution (women)



Note: Figure reports estimates of the impact of a masters qualification at different institutions on annual earnings at age 35, conditional on being in sustained employment, controlling for age, background and prior attainment. Results have been converted to percentage differences using a log-point conversion. Institutions are only included if they have at least 30 earnings observations at age 35. The bars represent the 95% confidence intervals.

It is important to note that we do not control for postgraduate subject when estimating the returns by university, and hence these returns will often be heavily driven by subject specialisation across institutions, which is much more prevalent than it is for undergraduate degrees (although we do of course control for *undergraduate* degree). This means comparisons between institutions require heavy caveats. For example, the top institution for men – London Business School – and the top institution for women – Nottingham Trent – both heavily specialise in high-returning LEM courses. On the other hand, the lowest-return institutions are nearly all specialist music and arts colleges, which offer almost exclusively subjects with very low average returns. To the extent that even successful artists and musicians may not always receive high earnings, the very low earnings returns amongst the bottom institutions also do not necessarily mean that they provide poor value for money for their students – these institutions may still be very successful at getting their graduates jobs in their chosen professions. Overall, 43% of institutions have positive point estimates of masters returns for women, but only around one in five institutions have statistically significant positive returns. For men one in five institutions have positive point estimates of returns, and around half of those have statistically significant positive returns.

Figure 19: Returns to masters degrees at age 35, by masters institution (men)



Note: Figure reports estimates of the impact of a masters qualification at different institutions on annual earnings at age 35, conditional on being in sustained employment, controlling for age, background and prior attainment. Results have been converted to percentage differences using a log-point conversion. Institutions are only included if they have at least 30 earnings observations at age 35. The bars represent the 95% confidence intervals.

### 6.3 Returns by *undergraduate* subject

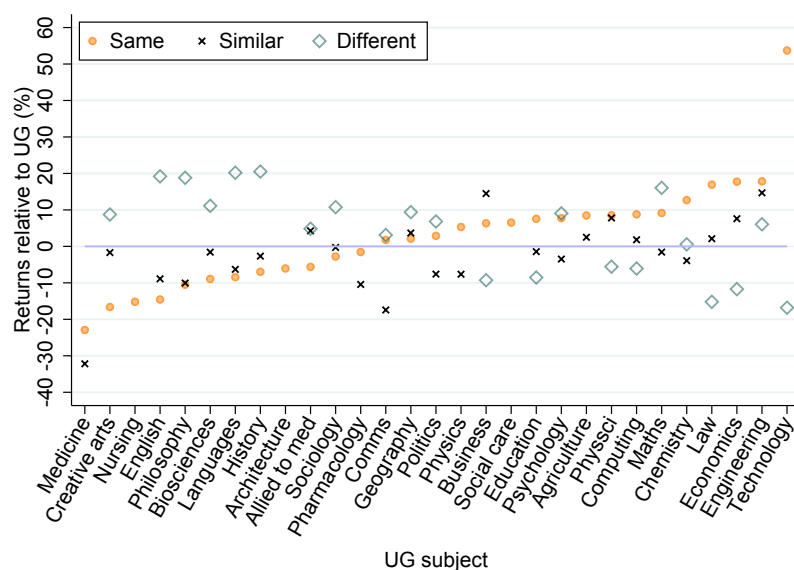
We now consider returns to a masters degree by *undergraduate* subject. From the point of view of the individual deciding on postgraduate study after they have finished their undergraduate degree, these estimates might seem particularly relevant. We expect these returns to differ from the average returns if returns to a masters course depend on whether the individual already has a qualification in that field. We may expect this to be the case, as courses can be complementary and individuals who have a related undergraduate degree may receive higher benefits, or conversely some masters qualifications may provide a greater earnings benefit for individuals who did a very different undergraduate degree. For example, doing a postgraduate course in business may open up a whole new field of (profitable) employment for those with an undergraduate degree in English literature, but provide less added benefit for those who already have an undergraduate degree in business.

Estimating returns for each masters course given each UG subject would be infeasible due to small sample sizes. Moreover, after each undergraduate degree, only a limited set of masters degrees

are commonly taken. We therefore will look at this heterogeneity by estimating the returns to doing a masters in the same subject, a similar subject (within the same subject group<sup>31</sup>) or an entirely different subject.

Figures 20 and 21 show these returns for women and men respectively. For both genders, we see a clear pattern where those undergraduate subjects that have very low or negative returns to doing a masters degree in the same subject, such as languages and English, overwhelmingly have strong *positive* returns to doing a masters in a different field.<sup>32</sup> For example, for women with an undergraduate degree in English, the returns to doing a masters degree in English compared with not proceeding to any further study is around -15%. However, the return to switching to a LEM- or STEM-based masters degree is close to +20%. For men, the return to an English masters degree for an English graduate is almost -30%, while the return to switching to a STEM or LEM field is +40%. These are dramatic differences.

Figure 20: Returns to masters degrees at age 35, by similarity to undergraduate subject (women)



Note: For each subject studied at undergraduate level, the figure shows the returns to doing a masters degree in the same, a similar (within the same subject group) and a different subject compared with the undergraduate degree. See the online appendix for a list of subjects included in each subject group (STEM/LEM/other).

On the other hand, students with an undergraduate degree where the return to doing a masters

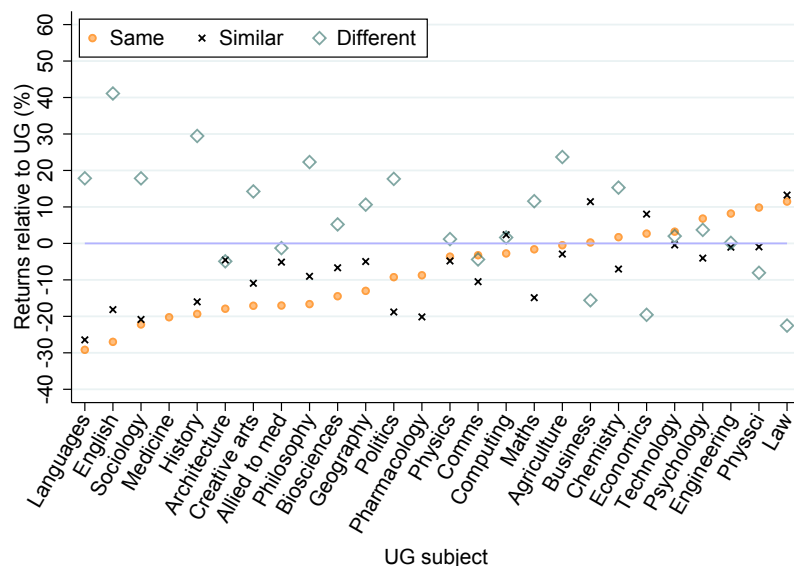
<sup>31</sup>Subject groups are defined as science, technology, engineering and maths (STEM), law, economics and management (LEM) and arts, other social sciences and humanities (other) which contains all remaining subjects. A detailed list of the subjects included in each of these categories is included in the online appendix.

<sup>32</sup>An exception is medicine, which has very negative returns to a masters degree. This is something of an unusual case, and is likely to be associated with people entering medical research rather than becoming a clinical doctor, the latter of which is a particularly well-paid option.

in the same subject is high – for example, economics or law – often experience *negative* returns to doing a masters in a different field. For example, women with an undergraduate law degree experience a positive return of 17% from a masters degree in law (compared with not proceeding to further study) but a negative return of -15% from switching to a new field. The patterns for switching to a masters subject that is similar to the undergraduate subject are a little bit mixed, but broadly speaking these returns are in between the estimates for doing the same subject and those for switching fields to a completely new area.

To summarise, these results suggest that for individuals with an undergraduate degree in a low-return subject, doubling down and staying in the same field for a masters degree is bad for earnings potential, while switching fields can significantly boost earnings outcomes. For those with an undergraduate degree in a high-return subject, doubling down tends to further increase earnings, while switching fields tends to reduce earnings. Of course, it is true, however, that individuals may not be trying to maximise their earnings potential and are instead looking to specialise in areas that will enable them to enter a career that they find interesting and fulfilling. This is something that we are not able to consider here.

Figure 21: Returns to masters degrees at age 35, by similarity to undergraduate subject (men)



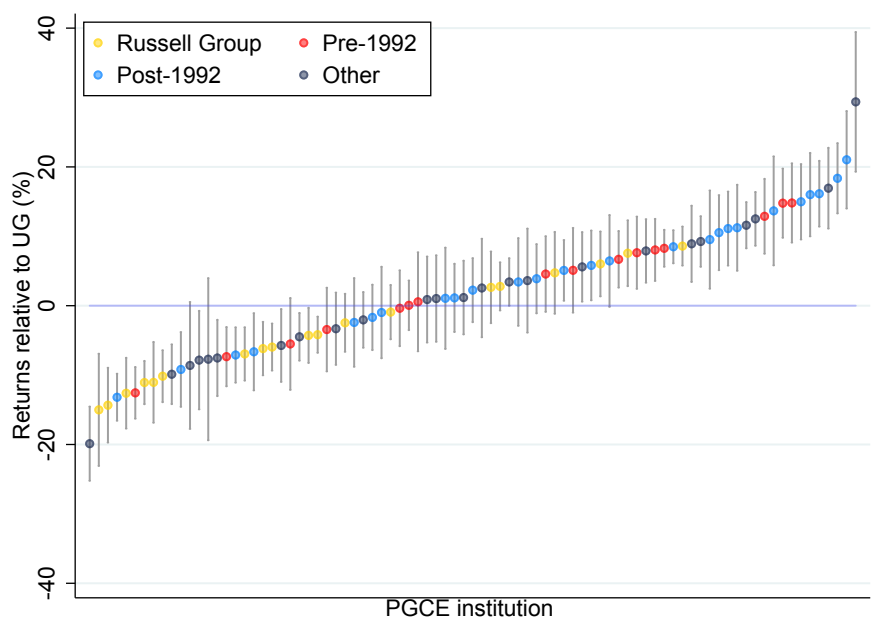
Note: For each subject studied at undergraduate level, the figure shows the returns to doing a masters degree in the same, a similar (within the same subject group) and a different subject compared with the undergraduate degree. See the online appendix for a list of subjects included in each subject group (STEM/LEM/other).

## 7 Heterogeneity in returns to PGCE degrees

We now turn to considering heterogeneity in returns to PGCE degrees. Unlike for masters and PhD degrees, there is no variation in subject studied at postgraduate level for PGCE students; we therefore only consider how returns vary by institution attended and by undergraduate subject studied.

Figure 22 shows the estimated returns by institution for PGCE degrees (Appendix Figure A13 is the equivalent figure for men, for whom the patterns are very similar). The results are quite stark: while Russell Group institutions tend to be among the highest-returning institutions for masters courses, the opposite is true for PGCE courses. A PGCE at some post-1992 institutions can increase earnings by around 20%, while for some Russell Group universities a PGCE reduces earnings by more than 15%. Although this might seem counter-intuitive, it can be explained by the selection of people into these different institutions. PGCE courses at the higher-status universities will typically attract individuals with high prior attainment and therefore a high outside option compared with teaching (i.e. relatively high-paying alternative careers). On the other hand, PGCE courses at lower-status universities will typically attract individuals with lower prior attainment and therefore worse outside options. A PGCE – which we saw earlier offers safe but relatively low wages on average – represents a very good option in terms of earnings at age 35 for the latter graduates, but a much less good option in terms of earnings for the former graduates.

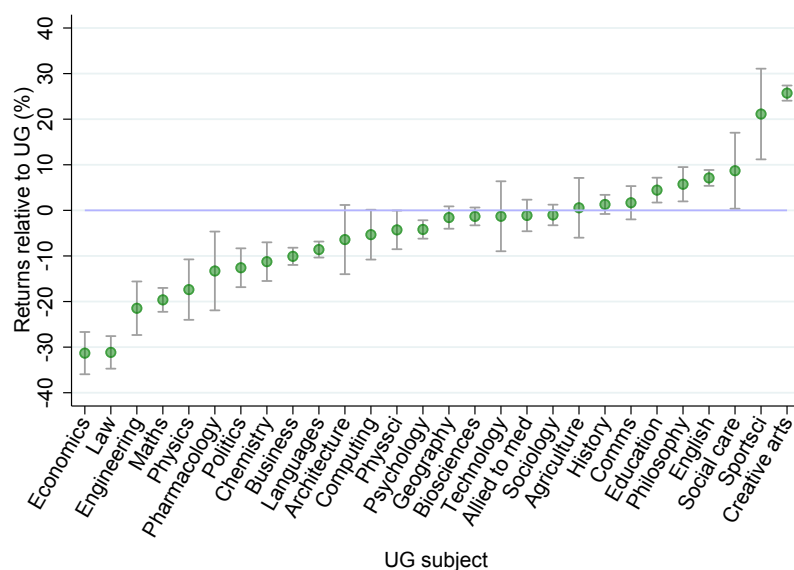
Figure 22: Returns to PGCE degrees at age 35, by PGCE institution (women)



Note: Figure reports estimates of the impact of a PGCE qualification at different institutions on annual earnings at age 35, conditional on being in sustained employment, controlling for age, background and prior attainment. Results have been converted to percentage differences using a log-point conversion. Institutions are only included if they have at least 30 earnings observations at age 35. The bars represent the 95% confidence intervals.

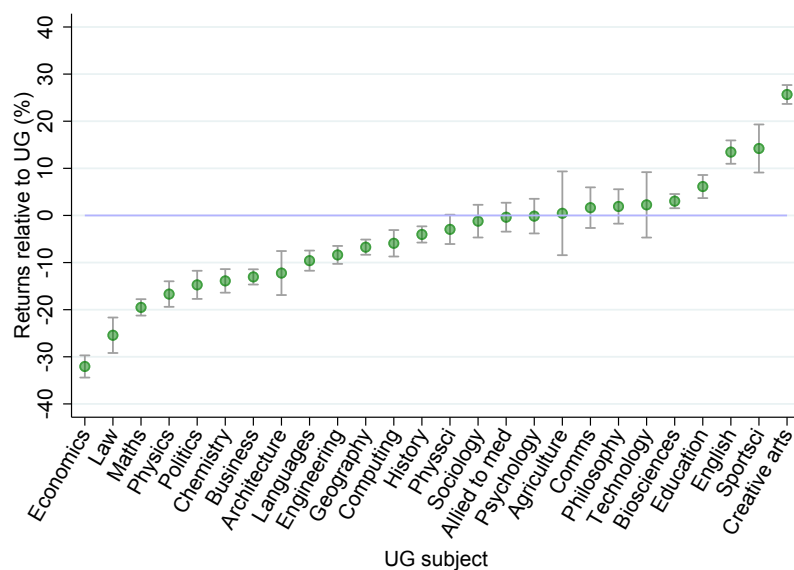
Finally, Figures 23 and 24 carry out a similar exercise to that in Section 6.3 and consider how the returns to PGCEs vary by the undergraduate subject of the individual. It is consistently the case that PGCEs have a high return for individuals with undergraduate degrees in low-returning subjects, and low returns for individuals with undergraduate degrees in high-returning subjects. For both women and men with an undergraduate degree in creative arts, a PGCE boosts earnings by more than 25%. For those with undergraduate degrees in economics, on the other hand, the returns are around -30%. Again, this is likely explained by the outside options available to these students. Importantly, for maths, physics and chemistry, the returns are substantially negative, which presumably helps to explain the acute teaching shortages in those areas.

Figure 23: Returns to PGCE degrees at age 35, by undergraduate subject (women)



Note: For each subject studied at undergraduate level, the figure shows the returns to doing a PGCE.

Figure 24: Returns to PGCE degrees at age 35, by undergraduate subject (men)



Note: For each subject studied at undergraduate level, the figure shows the returns to doing a PGCE. The bars represent the 95% confidence intervals.

## 8 Conclusion

This report provides new evidence on the selection into postgraduate courses and the earnings outcomes for those courses. The most striking finding, perhaps, is that while masters graduates on



average have higher earnings than graduates without postgraduate qualifications, once we account for differences in attainment and background characteristics we estimate a very low average return for women (1.5%) and even a small negative return for men (-2.3%). These returns are lower than those found in previous UK work using the LFS. This average result masks important variation, and many masters degrees yield positive returns. Masters degrees in law, economics and business are particularly lucrative.

Another important result in understanding the returns to masters degrees is how they vary by undergraduate subject studied. We show that for low-returning subjects, switching to a different field can yield very large positive returns, while ‘doubling down’ by studying a masters degree in the same subject can result in very large negative returns. For those with an undergraduate degree in a high-return subject, the opposite is true: doubling down yields very good positive returns, while switching fields can lead to large negative returns. Overall, for virtually all students, there are available masters courses that lead to strong positive returns.

For PhD degrees, the large differences in raw terms are again heavily reduced by the inclusion of controls for prior attainment. Our returns estimates suggest that PhD degrees boost earnings for women by around 7.5%, but *reduce* earnings for men by 9%. For women, there is not a huge amount of variation in returns by subject, with most yielding insignificant or small positive returns. For men, the range is larger, and mostly negative, with only business offering (marginally) significantly positive returns. One important point about the returns for PhD degrees is that there is some evidence that the returns continue to grow after age 35, as individuals gain more work experience. This suggests that the outlook might be more positive (especially for men) at later points in the life cycle. More generally, future research should consider the full life-cycle effects of postgraduate degrees.

For PGCEs, we find that average earnings are lower than for all other graduate groups, and appear to grow more slowly with age. Once we control for prior attainment, returns actually increase for PGCEs (unlike for masters and PhDs), highlighting the fact that PGCE qualifications typically attract undergraduates with lower earnings potential than the average person who does not proceed to any postgraduate study. Overall, we estimate a small positive return to PGCEs for women (1.2%) and a small negative return for men (-2.5%) at age 35.

We see that returns to doing a PGCE are lowest for those with the best outside options: those studying at the highest-status institutions or having studied undergraduate degrees that on average

lead to high earnings. For those studying at lower-status institutions and with undergraduate degrees in low-returns subjects, doing a PGCE can lead to large positive returns. This pattern helps to explain the drivers of negative selection into PGCE qualifications.

In general, we show that postgraduate degrees appear to offer insurance against bad labour market outcomes. This is particularly true for PGCE qualifications, which significantly increase the chances of having ‘good’ earnings by age 35, but simultaneously reduce the chances of achieving moderately high earnings (for example, above £50,000). This finding is also true for PhDs and, to a lesser extent, for masters degrees.

We also investigate access to postgraduate study and find that while large raw participation gaps do indeed exist, these are almost entirely explained away by prior attainment. This does not necessarily mean that if prior attainment were to improve amongst students from disadvantaged backgrounds then postgraduate fees would not generate barriers to access; it simply suggests that, currently, gaps in attainment in school and undergraduate degrees seem to be the binding constraint in terms of access to postgraduate courses among students from less well-off backgrounds. Clearly, there is considerable scope for future research in this area, in particular looking at trends in access since the many changes in undergraduate and postgraduate fees and loans that have happened since 2012, as well as looking at access to specific courses, such as masters in LEM subjects, which we show can be particularly lucrative yet are often some of the most expensive courses.

Our findings have several important implications. For students, the average returns to postgraduate degrees are perhaps less rosy than previously thought. However, more positively, for virtually all students there are *some* masters options they can do given their undergraduate subject that lead to positive earnings returns. This highlights the importance of subject and institution choice among postgraduate degrees for individuals who wish to maximise their earnings returns. For policymakers, the results may reopen questions about the generosity of student loans offered for postgraduate courses. It does, however, need to be kept in mind that there may be strong positive returns to society of some of the postgraduate courses that we find to have low returns in terms of earnings, such as courses leading individuals to work in research or teaching. The returns to PGCE degrees are also revealing about the return to teaching for people with undergraduate degrees in subjects such as maths, physics and chemistry, and help to explain the difficulties in recruiting teachers in these high-priority areas. While the result is intuitively obvious, the findings here are useful in providing concrete evidence to support that intuition.

Of course, our results only capture the *earnings* returns to postgraduate qualifications. As well as not capturing wider returns to society, we here also do not capture private returns to postgraduate study such as increased job satisfaction or fulfilment. While measurement of many of these things is a perennial problem, a clear avenue for future research which would address some of these questions is to study the occupations people with postgraduate degrees subsequently go into.

## References

- Altonji, Joseph G and Ling Zhong** (2019), ‘The labor market returns to advanced degrees’, mimeo.
- Arcidiacono, Peter, Jane Cooley and Andrew Hussey** (2008), ‘The economic returns to an MBA’, *International Economic Review*, 49 (3), 873–899.
- Belfield, Chris, Jack Britton, Franz Buscha, Lorraine Dearden, Matt Dickson, Laura van der Erve, Luke Sibieta, Anna Vignoles, Ian Walker and Yu Zhu** (2018a), *The Impact of Undergraduate Degrees on Early-Career Earnings*, Department for Education Report.
- , —, —, —, —, —, —, —, —, —, —, — and — (2018b), *The Relative Labour Market Returns to Different Degrees*, Department for Education Report.
- Conlon, Gavan and Pietro Patrignani** (2011), *The Returns to Higher Education Qualifications*, BIS Research Paper.
- Crawford, Claire, Lorraine Dearden, John Micklewright and Anna Vignoles** (2016), ‘Family background and university success: Differences in higher education access and outcomes in England’, *Oxford University Press*
- Grove, Wayne A and Andrew Hussey** (2011), ‘Returns to field of study versus school quality: MBA selection on observed and unobserved heterogeneity’, *Economic Inquiry*, 49 (3), 730–749.
- Lindley, Joanne and Stephen J Machin** (2011), ‘Rising wage inequality and postgraduate education’, IZA Discussion Paper 5981.
- Simkovic, Michael and Frank McIntyre** (2014), ‘The economic value of a law degree’, *Journal of Legal Studies*, 43 (2), 249–289.
- Titus, Marvin A** (2007), ‘Detecting selection bias, using propensity score matching, and estimating treatment effects: an application to the private returns to a master’s degree’, *Research in Higher Education*, 48 (4), 487–521.
- Walker, Ian and Yu Zhu** (2011), ‘Differences by degree: evidence of the net financial rates of return to undergraduate study for England and Wales’, *Economics of Education Review*, 30 (6), 1177–1186.

# Appendices

## A Descriptives

Table A1 : Summary statistics of our sample

	Whole sample	UG	PGCE	Masters	PhD
<i>Gender</i>					
Female	46.3	45.0	65.9	43.0	41.7
Male	53.7	55.0	34.1	57.0	58.3
<i>Participation</i>					
POLAR Q1 – lowest	8.0	8.1	9.9	6.4	7.3
POLAR Q2	13.2	13.3	15.3	11.3	12.3
POLAR Q3	18.4	18.5	19.6	17.0	17.1
POLAR Q4	24.4	24.5	24.1	24.2	24.9
POLAR Q5 – highest	36.1	35.6	31.2	41.0	38.4
<i>Ethnicity</i>					
Black	2.0	2.1	1.1	2.1	0.8
Asian	9.1	9.2	4.8	11.7	5.2
White	83.8	82.7	92.3	83.1	91.0
Other/missing	5.2	6.0	1.8	3.1	3.0
<i>Degree class</i>					
1st or distinction	8.7	6.5	5.9	15.3	44.6
2:1 or merit	45.0	42.3	51.7	54.8	48.3
2:2 or undiv 2nd	34.0	36.6	36.0	24.1	5.4
3rd, 4th, non-honours	7.0	8.4	4.3	2.6	0.4
Unclassified or other	4.8	5.6	1.9	2.8	1.1
Missing	0.6	0.7	0.2	0.4	0.2
<i>University type</i>					
Russell Group	31.2	26.7	31.0	48.5	66.4
Pre-1992	20.1	18.8	23.6	24.3	24.7
Post-1992	34.7	38.9	28.7	21.1	7.4
Other	14.0	15.6	16.7	6.1	1.5
<i>Subject group</i>					
STEM	43.6	41.4	36.3	51.4	84.0
LEM	19.6	22.0	7.7	17.5	2.0
Other	36.8	36.6	56.0	31.2	14.1

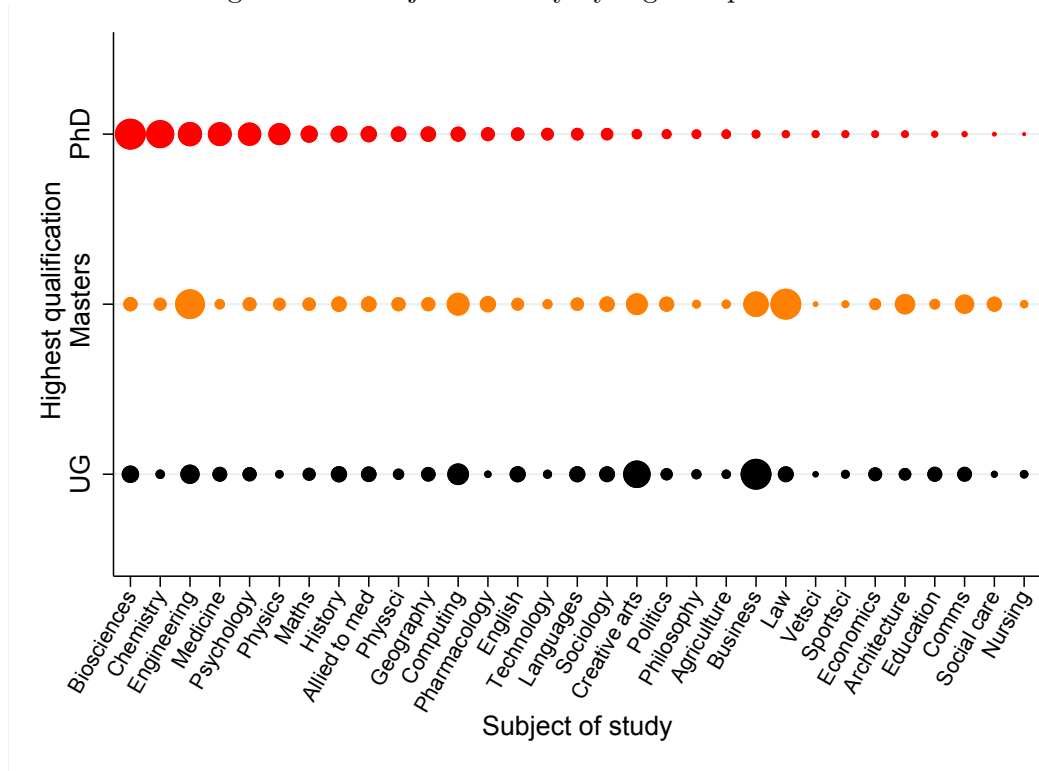
Note: The sample is based on column 6 of Table 1.

Table A2 : Highest qualification by undergraduate subject

	UG	PGCE	Masters	PhD
Agriculture	85.9	4.4	7.5	2.2
Allied to med	83.6	4.9	8.2	3.3
Architecture	76.3	1.5	21.9	0.3
Biosciences	63.4	11.0	14.5	11.1
Business	91.8	3.3	4.7	0.1
Chemistry	50.5	8.6	20.0	21.0
Comms	88.8	5.3	5.7	0.2
Computing	89.2	2.4	7.1	1.2
Creative arts	81.4	10.5	7.8	0.3
Economics	81.9	3.4	14.0	0.7
Education	85.9	11.4	2.5	0.2
Engineering	69.0	2.4	25.6	2.9
English	66.5	17.7	14.0	1.8
Geography	68.3	13.2	16.2	2.3
History	66.0	13.3	18.4	2.4
Languages	70.2	14.7	13.6	1.5
Law	65.9	2.0	31.6	0.4
Maths	68.9	11.4	14.4	5.3
Medicine	96.8	0.2	2.2	0.8
Pharmacology	44.1	1.9	46.1	7.8
Philosophy	66.0	15.9	16.0	2.2
Physics	48.1	8.3	25.5	18.2
Physsi	66.7	7.3	20.6	5.4
Politics	73.1	6.3	19.3	1.3
Psychology	64.1	12.0	16.1	7.8
Sociology	75.9	9.0	14.0	1.1
Sportsci	75.5	16.2	7.3	1.0
Technology	80.7	3.8	10.7	4.8

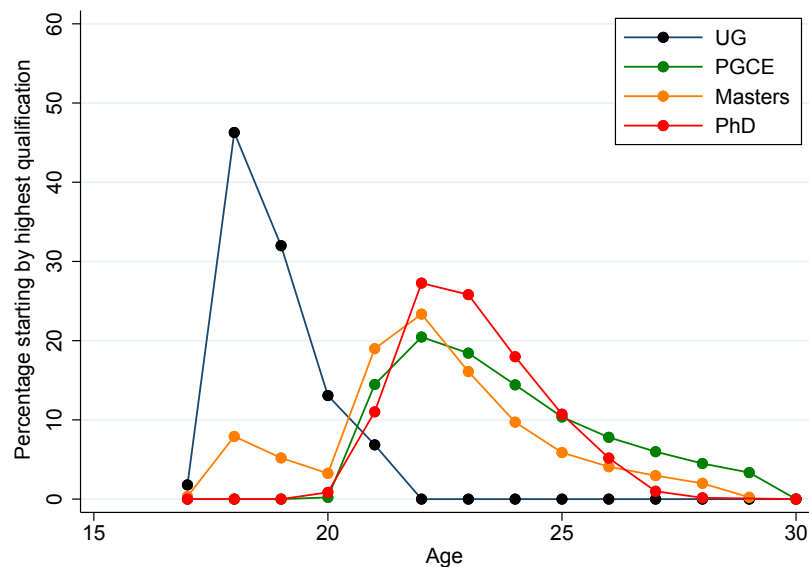
Note: Individuals are classified based on their *undergraduate* degree subject. Highest qualification is as defined in Section 2.2. The sample is based on column 6 of Table 1. The low proportion of medicine students doing postgraduate degrees is due to medicine courses being classified as undergraduate degrees, even when individuals do the full five or six years of a medicine degree (as the majority do).

Figure A1 : Subject of study by highest qualification



Note: Subject is based on what is studied for the highest qualification (which is not relevant for PGCEs). The marker size shows the proportion studying each subject *within* each qualification. Highest qualification is as defined in Section 2.2. The sample is based on column 6 of Table 1.

Figure A2 : Age started by highest qualification



Note: Highest qualification is as defined in Section 2.2. We exclude mature undergraduate students from our analysis, which is why no one starts their UG degree after age 21 here. The sample is based on column 6 of Table 1.

## B SES gaps in postgraduate participation

We are interested in the relationship between parental background and access to postgraduate degrees, and the extent to which differences in prior attainment can explain these relationships. As our data do not have any direct information on parental income, we instead use the rich NPD data to construct a proxy for socio-economic background. We can link university and earnings records to these rich NPD school records for individuals who sat their GCSE in England in or after 2002 (approximately born 1986 or after). In order to get the most complete measure of whether individuals will attend postgraduate courses, we choose to focus on the oldest cohort for whom we have NPD data in this analysis, which is the cohort who sat their GCSEs in 2002 and are aged approximately 30 years old when we last observe them in our tax and university records in 2016/17.

For this cohort, we construct an index of socio-economic background by combining information on free school meal (FSM) eligibility with very-local-level measures of socio-economic circumstances based on the area of residence at age 16. Specifically, we use an individual-level indicator of FSM eligibility at age 16, OA-level<sup>33</sup> measures of the proportion of individuals with Level 4 qualifications or higher, the proportion with no formal qualifications and the proportions working in higher and lower managerial and professional occupations<sup>34</sup> from the 2001 census, and an LSOA-level<sup>35</sup> measure of the proportion of children under the age of 16 who live in low-income households.<sup>36</sup> We combine these measures into a single index of socio-economic status (SES) using polychoric principal component analysis. We then split individuals into quintiles based on their SES index and compare access to postgraduate courses for individuals from the highest and lowest 20% of SES. As we do not have information on the home residence of private-school-educated individuals, we can only create this index for state-school pupils.

To estimate the percentage points gap in access to postgraduate courses between individuals from the top and bottom 20% of parental SES, and how much of this gap can be explained by prior attainment, we use a linear probability model (LPM). Specifically, we first run the following regression on the sample of individuals who are either in the top or in the bottom SES quintile:

$$PG_i = \alpha + \beta TopSESquintile_i + \epsilon_i \quad (6)$$

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<sup>33</sup>There are around 170,000 output areas (OAs) in England, which contain approximately 125 households each.

<sup>34</sup>NS-SEC level 1 and level 2 respectively.

<sup>35</sup>There are around 33,000 lower super output areas (LSOAs) in England, which contain approximately 650 households each.

<sup>36</sup>This measure comes from the Income Deprivation Affecting Children Index (IDACI).



where  $PG_i$  is an indicator for whether the individual has been enrolled in a postgraduate course by the end of our sample period and the coefficient  $\beta$  gives us the baseline percentage points difference in postgraduate attendance between children with parents in the highest SES quintile and those with parents in the lowest quintile (the omitted category). To investigate how much of this difference can be explained by children from higher socio-economic backgrounds performing better at school and university, we then sequentially add measures of prior academic attainment of the individuals:

$$PG_i = \alpha + \beta TopSESquintile_i + Z_i' \gamma + \epsilon_i \quad (7)$$

where  $Z_i$  is a vector of measures of prior academic attainment. We successively include measures of performance at age 11 (KS2 grades in maths, English and science), age 16 (total KS4 points, grades in English and maths, and indicators for the total number of GCSEs at each grade), age 18 (A-level points score, dummies for science, maths and social science A levels) and university level (degree class, subject and institution of undergraduate degree). The remaining differences in access between high- and low-SES individuals can be interpreted as the difference in access that cannot be explained by differences in academic attainment up to each point. Our final specification will therefore show the gap in postgraduate access that cannot be explained by differences in academic attainment at school or university.

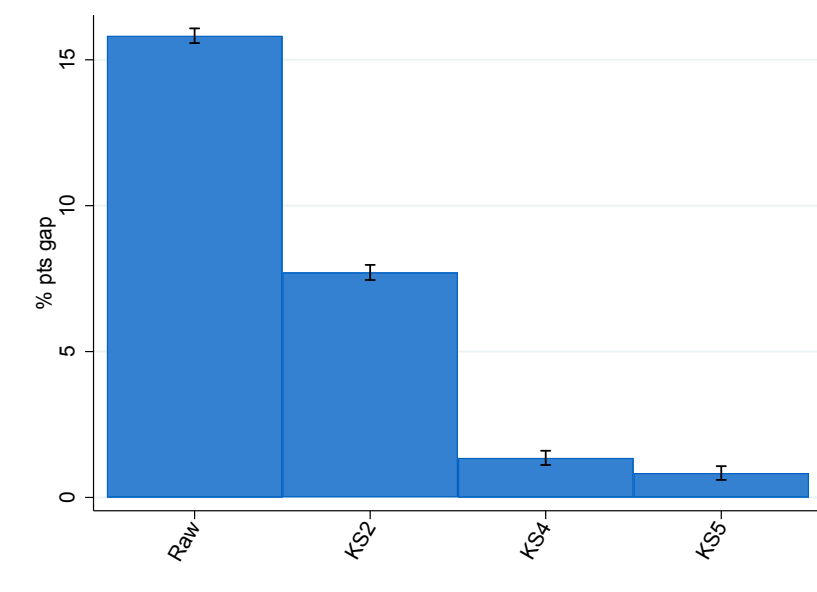
Results of this exercise are shown in the main text. Table A3 below shows the base level participation rates without adjusting for educational attainment by quintile of socio-economic background.

Table A3 : Participation rates by quintile of socio-economic background

	UG	Russell Group UG	Any PG	PGCE	Master's	PhD	Master's or PhD
SES Q1 (bottom)	18.1%	1.9%	3.8%	1.2%	2.9%	0.2%	2.9%
SES Q2	27.0%	3.6%	6.3%	1.9%	4.9%	0.5%	5.0%
SES Q3	35.4%	6.0%	9.2%	2.7%	7.2%	0.9%	7.4%
SES Q4	44.4%	9.8%	12.8%	3.5%	10.1%	1.4%	10.4%
SES Q5 (top)	58.4%	17.7%	18.1%	4.4%	14.7%	2.1%	15.2%
Private school	81.5%	43.9%	27.4%	4.6%	24.0%	3.1%	24.5%
Population	39.7%	10.2%	11.2%	2.9%	9.1%	1.2%	9.3%

Note: Participation rates for the 2002 GCSE cohort, using English state-school students only. SES is based on several measures combined into one continuous index, as described in more detail above. Each column shows the percentage of each quintile of SES who have started the degree listed in the column title by age 30. These participation rates also include individuals who start, but do not graduate from, a degree. The Masters/PhD column shows individuals who either have started a masters degree or a PhD. As most, though not all, of those who start a PhD have previously done a masters degree the rate of individuals who have either started a masters or a PhD is only slightly higher than the number of individuals who started a masters.

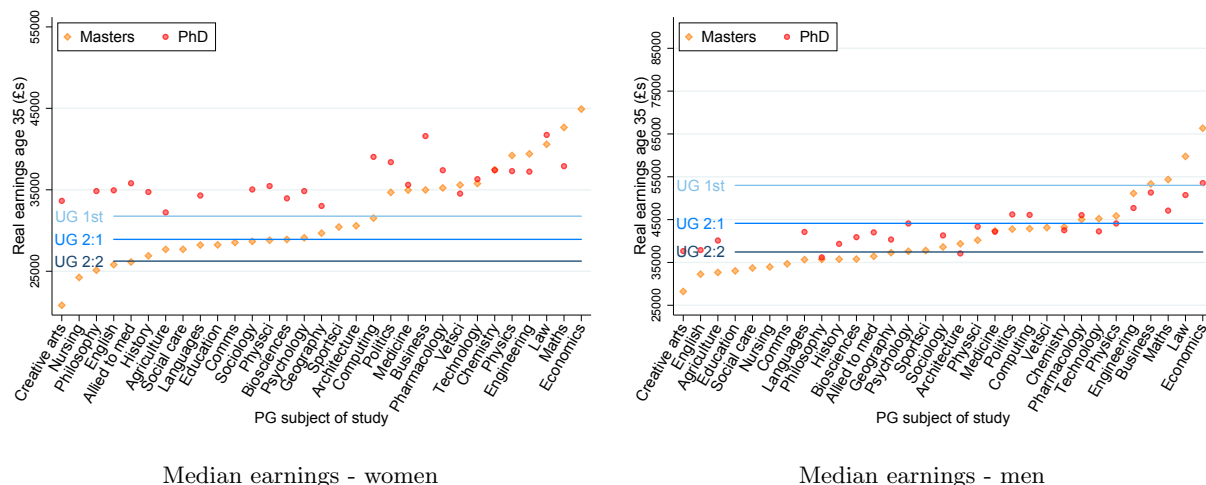
Figure A3 : Gap in UG participation at Russell Group universities, bottom vs top 20% of SES



Note: Results for the 2002 GCSE cohort, using English state-school students only. SES is based on several measures combined into one continuous index, as described in more detail in Appendix Section B. The first bar shows the raw percentage points gap in UG attendance between those from the top and bottom 20% of parental SES. The KS2, KS4 and KS5 bars add controls for age 11, 16 and 18 test scores respectively. See Appendix Section B for a full list of the controls included in each of the specifications. UG access is based on starting any standard UG degree course by age 30 at a Russell Group university.

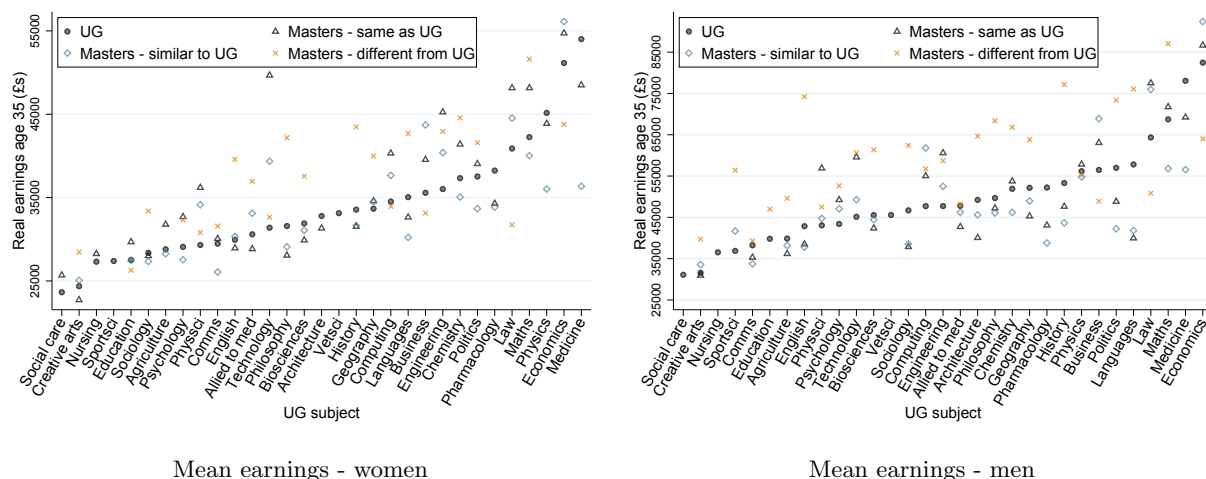
## C Earnings descriptives

Figure A4 : Median earnings for those in work at age 35 by highest qualification and postgraduate subject of study



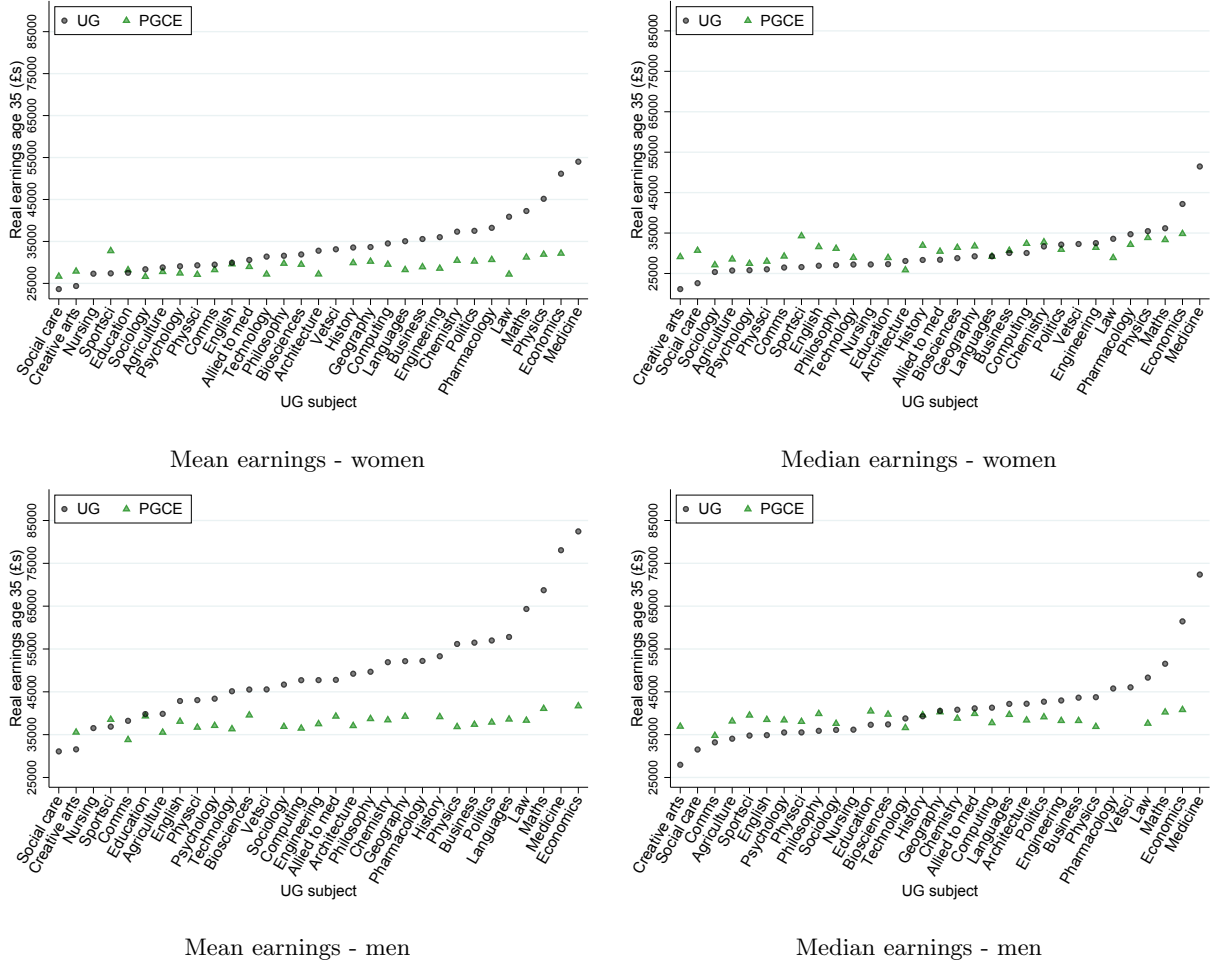
Note: Masters and UG are as defined in Section 2.2. The sample is based on all individuals in column 6 of Table 1 who are in sustained employment and have positive earnings at age 35. Groups where we observe fewer than 30 graduates with valid earnings observations at age 35 are excluded. The figures include PAYE and SA earnings, pooling across the years where we observe both of these (2013/14 to 2016/17). UG averages by degree classification exclude those who go on to PG study. All earnings are in 2018/19 prices.

Figure A5 : Earnings for those in work at age 35 by similarity of masters subject to undergraduate subject



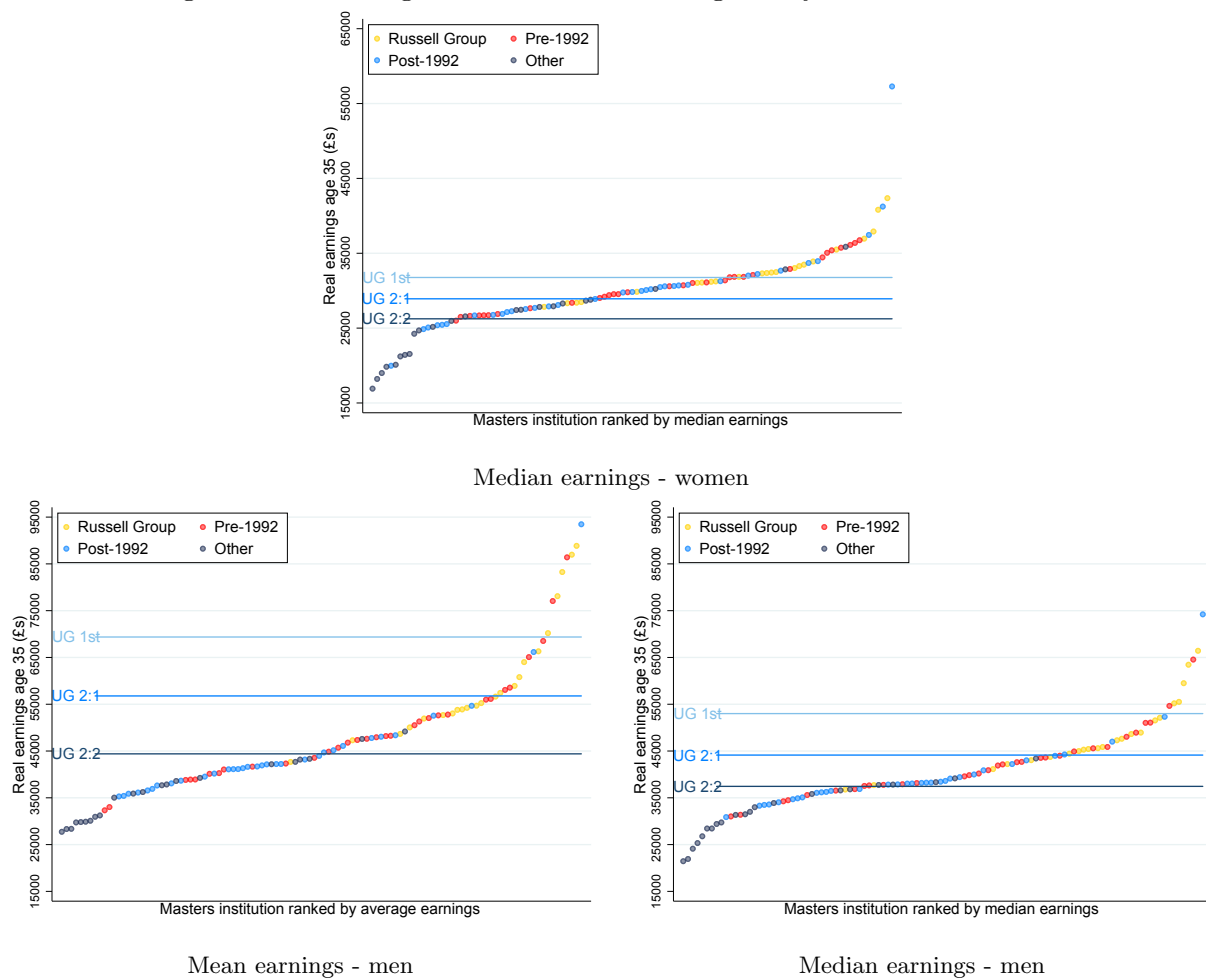
Note: Masters and UG are as defined in Section 2.2. The sample is based on all individuals in column 6 of Table 1 who are in sustained employment and have positive earnings at age 35. Groups where we observe fewer than 30 graduates with valid earnings observations at age 35 are excluded. The figures include PAYE and SA earnings, pooling across the years where we observe both of these (2013/14 to 2016/17). All earnings are in 2018/19 prices.

Figure A6 : Earnings of those in work at age 35 for PGCE graduates, by undergraduate subject



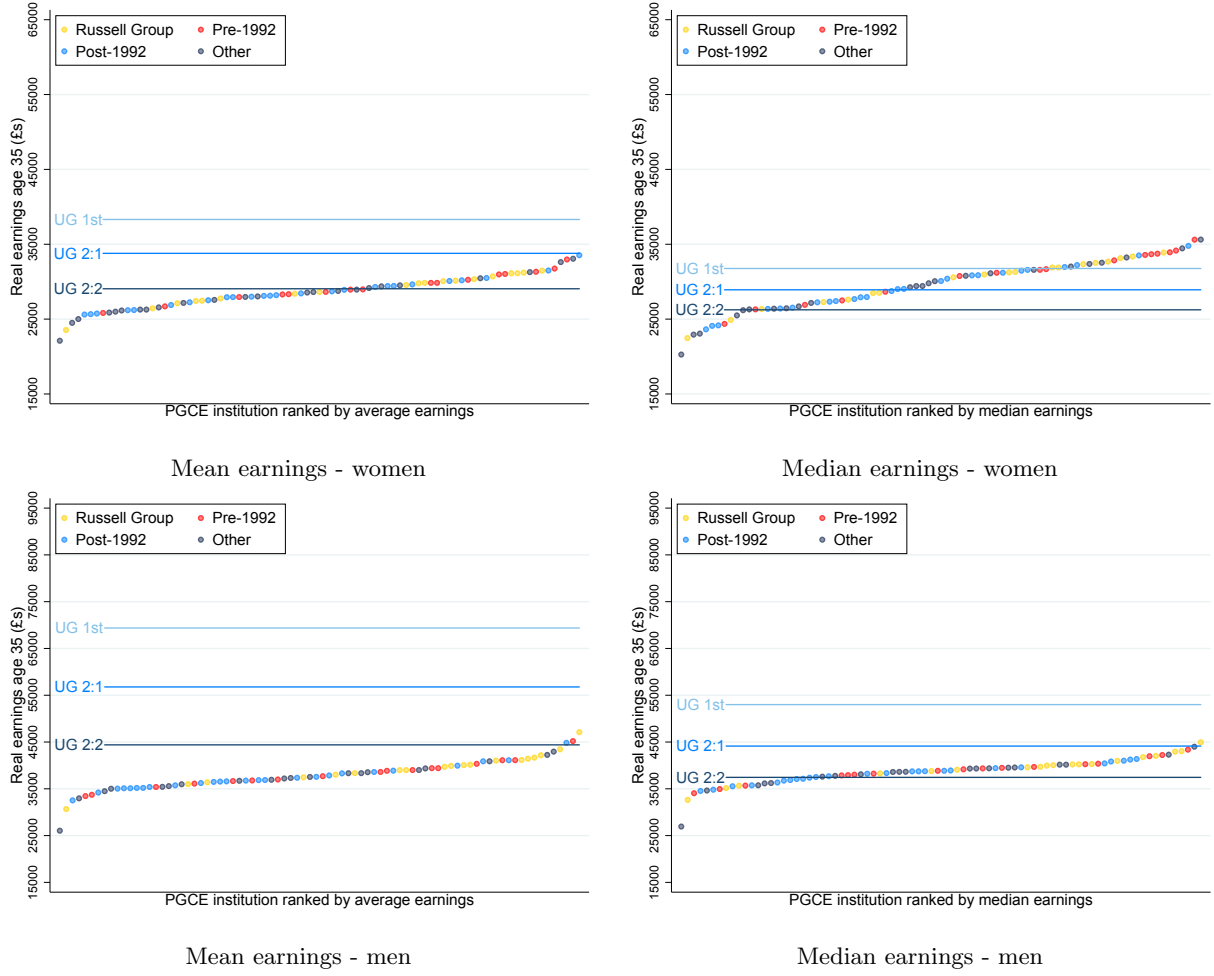
Note: PGCE and UG are as defined in Section 2.2. The sample is based on all individuals in column 6 of Table 1 who are in sustained employment and have positive earnings at age 35. Groups where we observe fewer than 30 graduates with valid earnings observations at age 35 are excluded. The figures include PAYE and SA earnings, pooling across the years where we observe both of these (2013/14 to 2016/17). All earnings are in 2018/19 prices.

Figure A7 : Earnings for those in work at age 35 by masters institution



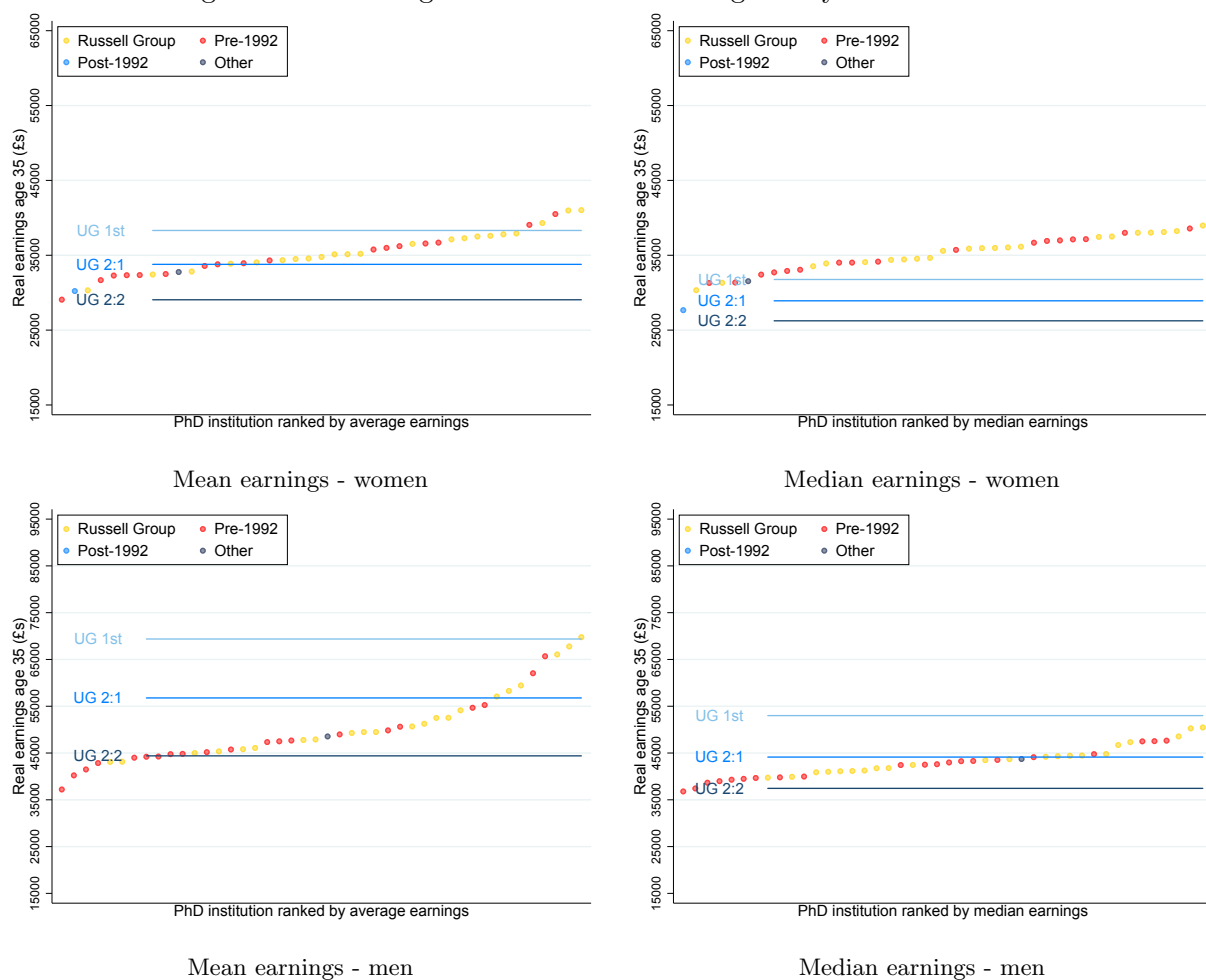
Note: Masters is as defined in Section 2.2. The sample is based on all individuals in column 6 of Table 1 who are in sustained employment and have positive earnings. Institutions where we observe fewer than 30 graduates with valid earnings observations at age 35 are excluded. The figures include PAYE and SA earnings, pooling across the years where we observe both of these (2013/14 to 2016/17). UG averages by degree classification exclude those who go on to PG study. All earnings are in 2018/19 prices. Institutions with average earnings above £100,000 are not shown on the figures.

Figure A8 : Earnings for those in work at age 35 by PGCE institution



Note: PGCE is as defined in Section 2.2. The sample is based on all individuals in column 6 of Table 1 who are in sustained employment and have positive earnings. Institutions where we observe fewer than 30 graduates with valid earnings observations at age 35 are excluded. The figures include PAYE and SA earnings, pooling across the years where we observe both of these (2013/14 to 2016/17). UG averages by degree classification exclude those who go on to PG study. All earnings are in 2018/19 prices.

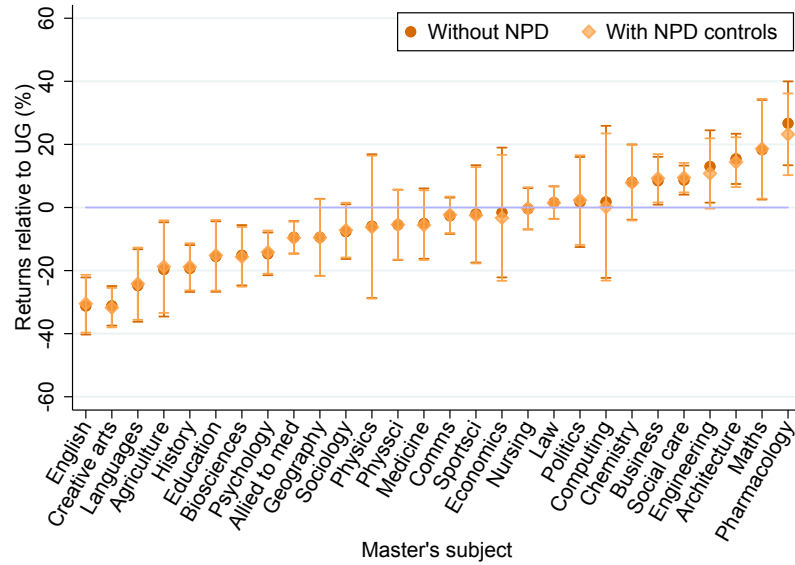
Figure A9 : Earnings for those in work at age 35 by PhD institution



Note: PhD is as defined in Section 2.2. The sample is based on all individuals in column 6 of Table 1 who are in sustained employment and have positive earnings. Institutions where we observe fewer than 30 graduates with valid earnings observations at age 35 are excluded. The figures include PAYE and SA earnings, pooling across the years where we observe both of these (2013/14 to 2016/17). UG averages by degree classification exclude those who go on to PG study. All earnings are in 2018/19 prices.

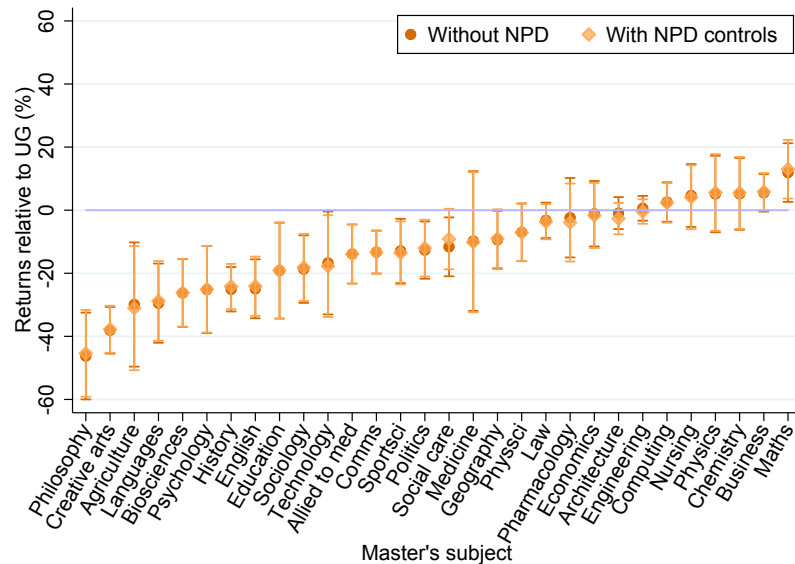
## D Robustness of results to including NPD variables

Figure A10 : Robustness to including NPD controls – returns by masters subject at age 30 (women)



Note: Sample is the 2002 GCSE cohort, using the earnings observation from the 2016/17 tax year when these individuals are approximately 30 years old. Additional NPD controls include UCAS tariff score, dummies for having a maths, science and social science A level, number of A\*, A, B and C grades at GCSE level and KS4 points score. The bars represent the 95% confidence intervals.

Figure A11 : Robustness to including NPD controls – returns by masters subject at age 30 (men)

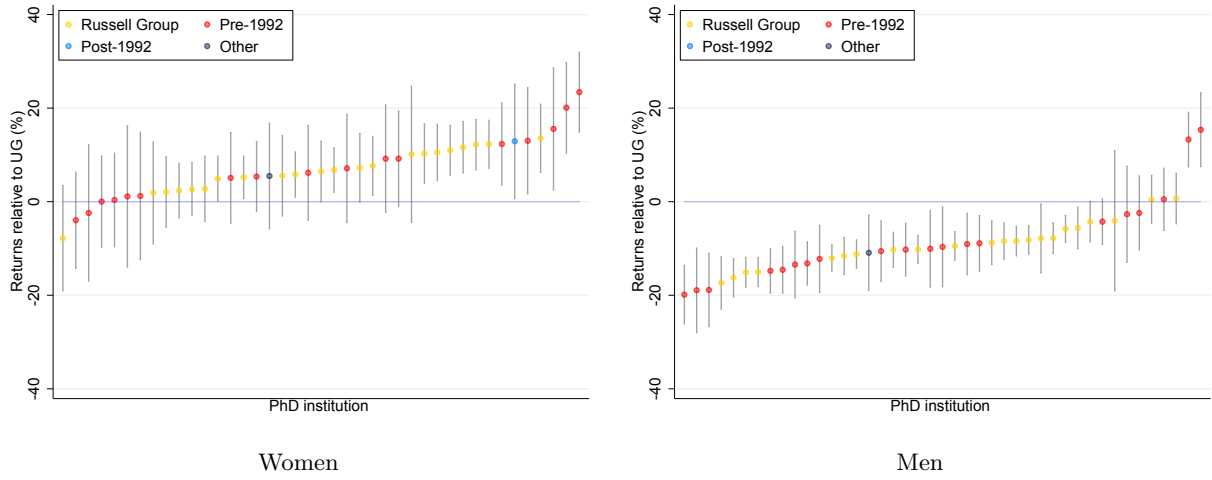


Note: Sample is the 2002 GCSE cohort, using the earnings observation from the 2016/17 tax year when these individuals are approximately 30 years old. Additional NPD controls include UCAS tariff score, dummies for having a maths, science and social science A level, number of A\*, A, B and C grades at GCSE level and KS4 points score. The bars represent the 95% confidence intervals.



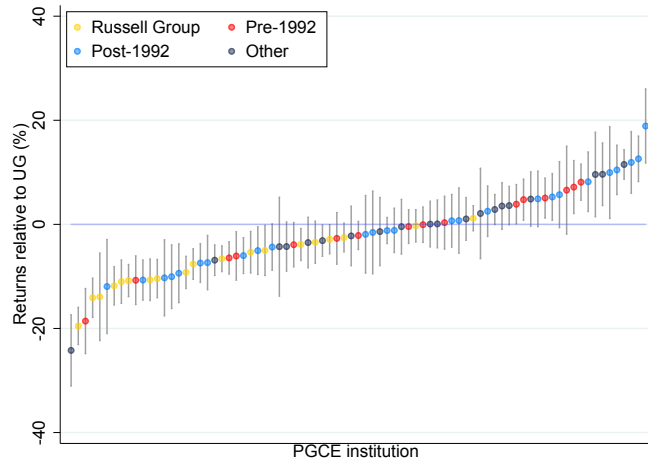
## E Additional results

Figure A12 : Returns to PhD degrees at age 35, by PhD institution (women left, men right)



Note: Figure reports estimates of the impact of a PhD qualification at different institutions on annual earnings at age 35, conditional on being in sustained employment, controlling for age, background and prior attainment. Results have been converted to percentage differences using a log-point conversion. Institutions are only included if they have at least 30 earnings observations at age 35. The bars represent the 95% confidence intervals.

Figure A13 : Returns to PGCE degrees at age 35, by PGCE institution (men)



Note: Figure reports estimates of the impact of a PGCE qualification at different institutions on annual earnings at age 35, conditional on being in sustained employment, controlling for age, background and prior attainment. Results have been converted to percentage differences using a log-point conversion. Institutions are only included if they have at least 30 earnings observations at age 35. The bars represent the 95% confidence intervals.



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